Aalto University
School of Engineering

Sami Vuokko

Safety Risk Modelling of Flight Planning in Commercial Operation of Performance Class B Aeroplanes

Thesis submitted for examination for the degree of Master of Science in Technology.

Espoo 5.9.2016

Supervisor: Professor Pentti Kujala
Instructors: D.Sc. (Tech.) Mikko Kanerva
M.Sc. (Tech.) Jyrki Laitila

Aalto University
School of Engineering

Aalto University, P.O. BOX 11000
00076 AALTO
www.aalto.fi

Abstract of Master's Thesis

Author	Sami Vuokko
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Abstract

In recent years, more stringent aviation regulations have demanded commercial air operators to put more emphasis on quantitative risk analysis methods as part of their safety management systems. The objective has been to promote aviation safety by identifying the risk factors applicable to the operations and mitigating their effectivity based on the risk analysis results. In particularly, the importance of proper flight preparation has been underlined by European Aviation Safety Agency for the commercial operation of single-engined turbine aeroplanes in instrumental weather conditions and at night. Yet, there are still not many comprehensive analysis methods, which would examine a flight as an entirety.

The aim of this thesis was to make a research about different risk analysis methods and find suitable means to develop new kind of risk models for the case examples, which were aerodrome and landing site determination and flight planning. Under particular interest were the questions of how much risk can vary between aeroplane types and in which extent is the overall risk mitigatable. The risk models are also supposed to be a basis for a risk tool that operators could utilise in their actual flight planning processes in the future. This risk tool would primarily be applicable to the operators of single-engined turbine aeroplanes but it is utilisable for other performance class B aeroplanes as well.

As an outcome, a novel weighted fuzzy hierarchy method was developed based on previous research. It calculates an individual risk level for each aerodrome and landing site along the route and an overall risk level for the entire planned flight. As a base, it uses risk models, which are hierarchical structures of each case example's applicable risk factors. An individual weight and set of membership functions were established for each risk factor in order to receive rational results. The weights and the membership functions were defined using the combination of expert judgement and statistics. Various example calculations showed that there are distinct variations in the risk levels of different kinds of operations. From the risk mitigation perspective, it was also noticed that the flight crew related risk factors have the most significant effect to the risk level. The method proved to be a usable and convenient tool to assess risk objectively and therefore further development and validation of this risk analysis method is recommended.

Keywords flight planning, risk, risk factor, hierarchy, fuzzy logic, SET-IMC

Aalto University
School of Engineering

Aalto-yliopisto, PL 11000
00076 AALTO
www.aalto.fi

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Tiivistelmä

Yhä tiukemmat ilmailuvaatimukset ovat viime vuosina vaatineet kaupallisia lento-operaattoreja panostamaan enemmän määrällisiin riskianalyysimenetelmiin osana heidän turvallisuudenhallintajärjestelmiään. Tarkoituksena on ollut ilmailun turvallisuuden parantaminen tunnistamalla operaatioihin liittyvät riskitekijät ja pienentämällä niiden vaikutusta riskianalyysin tuloksien perusteella. Euroopan ilmailuturvallisuusvirasto on painottanut riittävän lennonvalmistelun tärkeyttä erityisesti yksimoottoristen potkuriturbiinilentokoneiden kaupallisessa operoinnissa mittarilentokelillä ja yöaikaan. Silti ei ole olemassa montaa riskianalyysimenetelmää, joka ottaisi huomioon lentoa kokonaisuutena.

Tämän diplomityön tavoitteena on tutkia erilaisia riskianalyysimenetelmiä ja löytää sopivat keinot kehittämään uudenlaiset riskimallit esimerkkitapauksille, jotka ovat lentokentän ja varalaskupaikan määrittäminen ja lennonsuunnittelu. Erityisenä mielenkiinnonkohteena ovat kysymykset, kuinka paljon riski voi vaihdella riippuen lentokonetyypistä ja missä määrin kokonaisriski on pienennettävissä. Riskimallien on tarkoitus myös toimia perustana riskityökalulle, jota operaattorit voisivat tulevaisuudessa käyttää todellisissa lennonsuunnitteluprosesseissaan. Tämä riskityökalu olisi pääasiassa tarkoitettu yksimoottoristen potkuriturbiinilentokoneiden operaattoreille, mutta se on sovellettavissa myös muihin suoritusarvoluokkaan B kuuluviin lentokoneisiin.

Aiemman tutkimuksen pohjalta kehitettiin uudenlainen, sumeaa logiikkaa ja painokertoimia hyödyntävä hierarkkinen menetelmä. Se laskee yksilöllisen riskitason reitin varrella oleville kullekin lentokentälle ja varalaskupaikalle ja kokonaisriskitason koko lennolle. Pohjana se käyttää riskimalleja, jotka ovat hierarkkisia rakenteita esimerkkitapausten riskitekijöistä. Yksilöllinen painokerroin ja sarja jäsenfunktioita määritettiin kullekin riskitekijälle, jotta saataisiin rationaalisia tuloksia. Painokertoimet ja jäsenfunktiot määriteltiin sekä asiantuntija-arvioiden että tilastojen avulla. Useat esimerkkilaskelmat osoittivat, että erilaisilla operaatioilla on selviä eroja riskitasoissa. Riskin pienentämisen näkökulmasta huomattiin myös, että lentomiehistöön liittyvillä riskitekijöillä on kaikkien suurin vaikutus riskitasoon. Menetelmä osoittautui käyttökelpoiseksi ja sopivaksi menetelmäksi riskin arvioimiseen objektiivisesti ja tämän johdosta tämän riskianalyysimenetelmän jatkokehittämistä ja validointia suositellaan.

Avainsanat lennonsuunnittelu, riski, riskitekijä, hierarkia, sumea logiikka, SET-IMC

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Abbreviations

AFIS	Airport Flight Information Service
AHP	Analytical Hierarchy Process
AIP	Aeronautical Information Platform
ALARP	As Low as Reasonably Practicable
ALRV	Approach and Landing Risk Value
ALS	Approach Lighting System (F = Full, I = Intermediate, B = Basic, N = No)
APV	Approach Procedure with Vertical Guidance
ARMS	Aviation Risk Management Solutions
ASRM	Aviation Safety Risk Model
BBN	Bayesian Belief Network
CAA	Civil Aviation Authority
CAAP	Civil Aviation Advisory Publication
CAO	Civil Aviation Order
CAR	Civil Aviation Regulation
CASA	Civil Aviation Safety Authority
CAT	Commercial Air Transport
CFIT	Controlled Flight into Terrain
CPT	Conditional Probability Table
CRM	Crew Resource Management
EASA	European Aviation Safety Agency
EDTO	Extended Diversion Time Operations
ERC	Event Risk Classification
ETA	Event Tree Analysis
ETOPS	Extended-range Twin-engine Operational Performance Standards
FAA	Federal Aviation Administration
FAR	Federal Aviation Regulation
FCE	Fuzzy Comprehensive Evaluation

FIS	Fuzzy Inference System
FMEA	Failure Mode and Effects Analysis
FMECA	Failure Mode, Effects and Criticality Analysis
FORAS	Flight Operations Risk Assessment System
FTA	Fault Tree Analysis
GA	General Aviation
HFACS	Human Factors Analysis and Classification System
IFR	Instrumental Flight Rules
IMC	Instrumental Meteorological Conditions
LDA/R	Landing Distance Available/Required
MEL	Minimum Equipment List
MOPSC	Maximum Operational Passenger Seating Configuration
MSA/H	Minimum Sector Altitude/Height
MTOW	Maximum Take-off Weight
NASA	National Aeronautics and Space Administration
OEI	One Engine Inoperative
OML	Operational Multi-crew Limitation
PRA	Probability Risk Assessment
RIE	Rectification Interval Expiry
RPN	Risk Priority Number
RVR	Runway Visual Range
SE	Single Engine
SET	Single-engined Turbine
SIRA	Safety Issue Risk Assessment
SMS	Safety Management System
SOP	Standard Operating Procedures
TORA/R	Take-off Run Available/Required
VFR	Visual Flight Rules
VMC	Visual Meteorological Conditions

1 Introduction

1.1 Theoretical Background

A quantitative risk analysis methods utilising probability risk assessment (PRA) have become increasingly more common in the aviation sector as a part of safety management systems (SMS) [1]. More stringent aviation regulations aim to promote safety-based culture among aircraft operators. New systems and concepts have to go through a profound analysis before they can be adopted as part of daily aircraft operations [2].

However, a level of uncertainty has always been a concern in the analyses. An accident is always a result of several different factors and quantifying a risk for that is rarely straightforward. One has to be able to take in to account all the root causes and weight their individual consequences accordingly. The estimation of likelihood for each factor to happen is often a combination of mathematics and experts' judgement.

Many tools for assessing risk have been developed. These include e.g. decision/fault tree analysis, sensitivity analysis and Monte Carlo simulation. The methods can be further divided to qualitative and quantitative phases. [3] For example, European Aviation Safety Agency (EASA) has previously used the fault tree analysis in its rulemaking processes [4].

Particularly demanding are the cases having little operational statistical data. Generating rational quantitative data for objective decision making is challenging because intuitive judgement is always a subjective matter. Using a fuzzy rule-based analysis method, many issues of traditional qualitative and quantitative methods can be resolved. It enables safety analysts to combine imprecise, ambiguous, qualitative information with quantitative data in a consistent manner. [5] As a result, the method can output justified numerical risk levels for different risk factors emerged during a flight operation.

1.2 Objectives and Structure of the Thesis

The thesis has a target of answering to the following research questions:

1. How much does the exposed risk vary between aeroplane types?
2. How much can the risk be mitigated by careful flight planning?
3. What is the effect of cruise altitude to the overall exposed risk during a flight?
4. What is the practicality of a fixed risk period applied to single-engined aeroplanes?
5. What are the risk factors when determining an emergency landing site and how these risks can be validated?

The goal of the thesis is to make a broad research about the available risk analysis methods and analyse their applicability to the case examples defined by the research questions. The plan is to choose one or two most suitable methods and use them to create risk models for group of performance class B aeroplanes. The examined analysis methods are e.g. Monte Carlo simulation and Fuzzy rule-based analysis.

The current analysis methods used in aviation industry are identified and the goal is to find and, if necessary, further develop new practical methods, which could help the task of risk assessments in this field. Some tools to validate the risk assessment results are also attempted to be found.

The case examples used in this risk study are aerodrome and landing site determination and flight planning. These are a vital part of a flight preparation and also safety management as an aeroplane has to have a suitable place to land if engine malfunction(s) occur during a flight. Earlier, some studies have suggested that a maximum of 15 minutes risk period should be used with single-engined turbine aeroplanes [6]; i.e. an emergency landing site is allowed to be out of reach only a maximum of 15 minutes of a flight. The applicability of this recommendation will be evaluated for these aeroplanes in this thesis. Furthermore, an appropriate landing site is a vital risk mitigation measure and thus its proper determination using risk models will also be evaluated in the thesis.

The input data used in the risk models consists of applicable incident data and aviation experts' experience. The incident data will be gathered from publicly available aviation safety studies as seen appropriate and aviation experts will be consulted mainly in civil aviation authority of Finland (CAA Finland) as well as in some other companies. The consultation is conducted by surveys to get a broader insight of applicable risks and their relative importance.

1.3 Limitations

As earlier mentioned, the study will focus on the risks associated with the operation of performance class B aeroplanes. A performance class B aeroplane is defined as an aeroplane powered by propeller engines with a maximum operational passenger seating configuration of nine or less and a maximum take-off mass of 5 700 kg or less [7]. The considered aeroplane models are e.g. Piper PA-31 Navajo, Pilatus PC-12 and Beechcraft King Air 100.

The amount of risk analysis methods introduced in the literature review will be limited to 5-10 methods and their selection will be based on author's discretion. 1-2 most appropriate methods will further be used in the experimental part. The suitability of a method is evaluated by its novelty, accuracy and needed workload. A set of computer simulation software, e.g. MATLAB®, will be used to the extent possible.

2 Commercial Operation of Performance Class B Aeroplanes

2.1 Current Regulation Status in Different Continents

In this section, air operations laws are studied in the context of operating specialities and limitations of performance class B aeroplanes. These specialities and limitations are further limited to subjects, which are relevant to the case examples in this thesis. The study has been divided for two-engined and single-engined aeroplanes. The considered air operations laws are EASA, FAA and CASA regulations. Other regulation structures are excluded in this study.

2.1.1 Two-engined Aeroplanes

Europe

According to EASA Air Operations regulations [7], performance class B aeroplanes shall not be operated over a route that contains a point further from an adequate aerodrome, under standard conditions in still air, than the distance flown in 120 minutes at the one engine inoperative (OEI) cruise speed or 300 NM, whichever is less (CAT.OP.MPA.140). When comparing to performance class A aeroplanes, the 120 minutes time limitation can be extended up to 180 minutes for small jet aeroplanes (maximum operational passenger seating configuration (MOPSC) $\leq$ 19 or maximum take-off weight (MTOW) < 45 360 kg) with a separate authority approval. However, for large jet aeroplanes (MOPSC $\geq$ 20 or MTOW $\geq$ 45 360 kg), the time is limited to 60 minutes but this can also be extended with an extended-range twin-engine operational performance standards (ETOPS) approval.

If OEI situation occurs during en-route flight, the aeroplane shall be capable of continuing flight at or above the relevant minimum altitudes for safe flight to a point of 1 000 ft above an aerodrome at which the performance requirements can be met (CAT.POL.A.315). In comparison, for performance class A aeroplanes the limit is 1 500 ft with a positive flight path gradient (CAT.POL.A.215).

In landing situation, for destination and alternate aerodromes, the landing mass shall allow a full stop landing from 50 ft above the threshold within 70 % of the landing distance available (LDA) in the case of dry runway (CAT.POL.A.330). In the case of wet runways, the LDA shall be equal to or exceed the required landing distance multiplied by a factor of 1.15. Grass runways should be handled with this same factor. For contaminated runways, the factor is 1.0 (CAT.POL.A.335). In contrast, for performance class A jet aeroplane, the numbers are 60 %, 1.15 and 1.15 respectively (CAT.POL.A.230/235).

United States

Unlike EASA, which categorises aeroplanes as either performance class A, B or C based on the engine type, seating configuration and maximum allowable take-off weight, Federal Aviation Administration's (FAA) Federal Aviation Regulation (FAR) parts 121/135 [8] divide performance requirements based on the type of commercial operation that is being conducted (121 for scheduled and 135 for commuter and on-demand operations) and aircraft's engine type (reciprocating or turbine). Thus FAR is more stringent because both the part 121 and 135 performance rules apply to all aircrafts, regardless of size or seating configuration.

To make a basic comparison between EASA's regulations for performance class B aeroplanes and FAA's equivalent regulations, an assumption must be made that performance class B aeroplanes are used for commuter operations and thus part 135 regulations must be complied. According to § 135.364, commuter aeroplanes (to include both jet and turboprop aeroplanes) are allowed to perform a flight, in which the aeroplane will be a maximum of 180 minutes flight time from an adequate airport using OEI speed outside the continental United States. This is one hour more than the value EASA is allowing for performance class B aeroplanes.

The paragraph § 135.398 includes the performance limitations of commuter category aeroplanes. It states that the commuter category aeroplanes must comply the same landing limitations as turbine-engine-powered large transport category aeroplanes listed in § 135.385 and § 135.387. These requirements are similar to limitations of performance class A aeroplanes in EASA's regulation structure.

Australia

Australian Civil Aviation Safety Authority (CASA) categorises aeroplanes based on their maximum take-off weight and the type of operation (e.g. private, aerial work, charter and regular public transport operations). The regulations are established in Civil Aviation Regulations (CARs), Civil Aviation Orders (CAOs) and Civil Aviation Advisory Publications (CAAPs).

Regarding the threshold time, CAAP 82-1(1) [9] gives information that a maximum of 60 minutes flight time from an adequate airport using OEI speed is allowed for aeroplanes with two turbine engines (turboprop or jet engine). It can be extended with a special extended diversion time operations (EDTO) approval or having more than two engines. The maximum achievable threshold time is 180 minutes.

CAO Section 20.7.2 [10] gives further performance limitations for multi-engined aeroplanes having a maximum take-off weight not in excess of 5 700 kg. Section 5.3 states that in OEI situation the aeroplane shall be capable of returning to the nearest aerodrome with 2 000 ft vertical clearance from all terrain and obstructions. This regulation and the above mentioned 60 minute threshold time are two times stricter than the relevant values in EASA structure.

On the other hand, the landing limitations in Section 6 [10] seem to be slightly looser as the landing distance available on the runway of intended landing shall be equal to, or greater than, the landing distance required for the aeroplane concerned without any extra margins. This regulation is also allowed to be neglected in an emergency situation.

2.1.2 Single-engined Aeroplanes

Europe

So far, EASA's regulations have permitted single-engined turbine and piston aeroplanes to operate commercially only in visual meteorological conditions (VMC) due to excessive risk related to the operation in instrumental weather conditions and at night (SET-IMC) [7]. However, a new rulemaking task RMT.0232-0233 has been in process and in late 2015, an Opinion 06/2015 [4] was published to propose the allowance for commercial operation of single-engined turbine aeroplanes also in instrumental weather conditions and at night. Until now, some operators may have been able to conduct such operations under the conditions set out in the existing exemptions granted by Member States [7].

In VMC operations, single-engined aeroplanes have to follow same regulations as established for performance class B aeroplanes. Yet, as stated in CAT.OP.MPA.136 and CAT.POL.A.320, the aeroplane shall only be operated along routes, or within areas, where surfaces are available that permit a safe forced landing to be executed in the event of engine failure. Similarly to twin-engined aeroplanes, following an engine failure, an aeroplane should be capable of reaching a point (1 000 ft above the intended landing area if not otherwise specified), from which a safe forced landing can be made.

The distinction between twin-engined and single-engined aeroplanes is that for twin-engined aeroplanes alternate aerodromes must have been predetermined along the route and the aeroplane must stay within 120 minutes flying time from those using the OEI speed. Single-engined aeroplanes on the other hand must always have a landing site within a gliding distance and this landing site does not necessary have to be an aerodrome as it can also be a plain field suitable for emergency landing.

Opinion 06/2015 [4] would introduce a new SET-IMC special approval for operators to be applied from the competent authority. If it was published as it is now proposed, this new approval would allow a fixed 15 minutes risk period to be utilised per flight. This means that the aeroplane is allowed to be a maximum of 15 minutes per flight out of reach a suitable emergency landing site. Alternatively, the operator could make a separate risk assessment for each route and ensure that the total risk level remains under the target fatal accident rate of $1.3 \cdot 10^{-6}$ per flight hour.

The suggested 15 minutes risk period limitation for single-engined turbine aeroplanes and 120 minutes flight time from adequate aerodrome limitation for twin-engined aeroplanes are not directly comparable because they have a different meaning as Figure 1 illustrates. The comparable value for single-engined turbine aeroplane is the time used to glide from cruise altitude to 1 000 ft above the intended landing area with the best gliding ratio and speed after the engine failure. This is dependent of aeroplane model and for example for Pilatus PC-12 it is about 34 minutes with a cruise altitude of 26 000 ft, a glide ratio of 16:1 and a gliding speed of 116 KIAS [11]. In other words, Pilatus PC-12 cannot be operated further from the nearest adequate aerodrome than the distance flown in 34 minutes at the best gliding speed if still air conditions are assumed and the aeroplane is flying on its' cruise altitude FL260. Naturally this value becomes smaller in take-off and landing situations where the current altitude is lower. Thus the risk period gives some flexibility in the compliance of the rule.

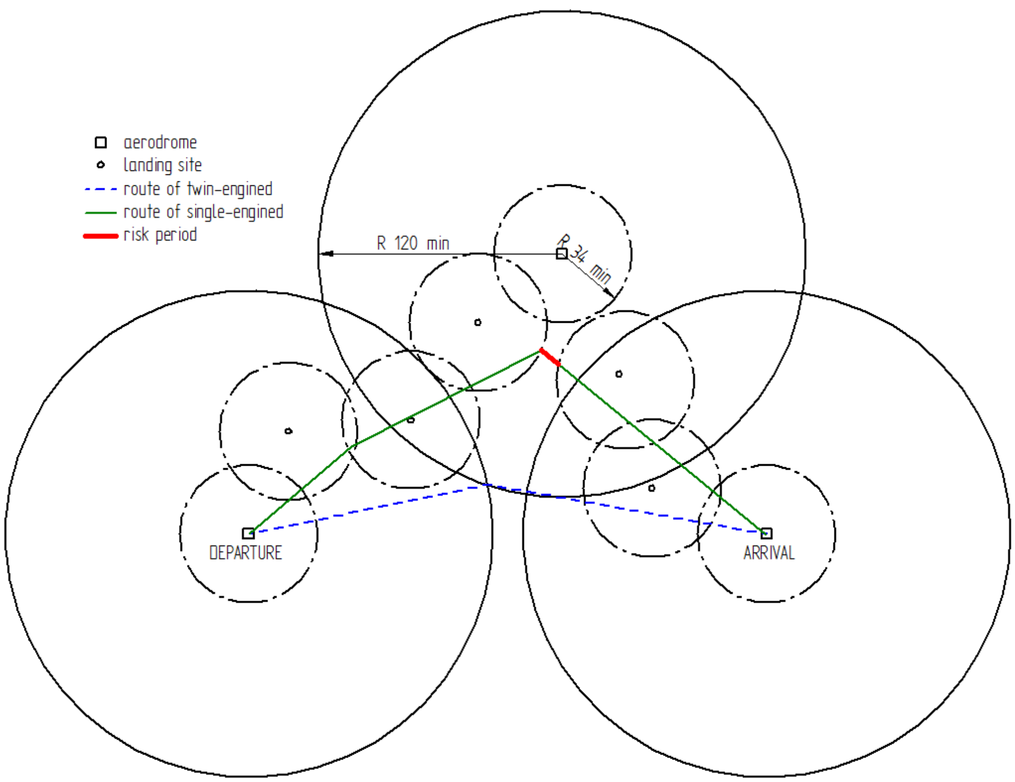


Figure 1. Relation between the risk period and the maximum flight time from adequate aerodrome.

Regarding the determination of landing site's acceptability, the Opinion 06/2015 [4] gives several criteria for operators to be considered. For example, the width of the landing area should be at least 45 m and the length should allow the aeroplane to completely stop within the available surface, taking into account the slope and the type of the surface. It is also recommended to select, if possible, landing sites with a circular shape as they allow multiple approach paths depending on the wind and obstacles around the landing area.

On the other hand, if the landing site was an aerodrome, the same landing requirements would apply to single-engined aeroplanes as for any other performance class B aeroplanes (CAT.POL.A.330/335).

United States

Unlike EASA, FAA has permitted commercial operations of single-engined turbine as well as piston aeroplanes in instrumental flight rules (IFR) and at night since 1997 under Part 135 regulations. The FAA justified the new allowance by diminishing accidents caused by the VFR flights turned into IMC flights in regions like Alaska.

There's no specific approval to be applied for single engine IFR (SEIFR) but multiple additional requirements exist for single-engined aeroplanes like equipment, maintenance and pilot certification requirements. There are also no risk period limitations and the performance requirements are basically the same as for any other commuter class aeroplanes. However, the regulation § 135.181 demands that a single-engined aeroplane may be operated over-the-top-of-clouds conditions only if the forecasted weather allows flight under VFR and under the ceiling (if a ceiling exists) and that a descent under VFR is possible if the engine fails. [8]

Notable is also the fact that there are no specific requirements about the need for predetermined emergency landing sites along the route. Thus the same alternate aerodrome requirements apply to single-engined aeroplanes as well.

Australia

CASA approves single-engined aeroplanes for charter or regular public transport operations that involve the carrying of passengers for hire or reward under night VFR and IFR if the operator is approved by CASA to conduct the operations (ASETPA) and the operations are conducted with a turbine-powered aeroplane approved by CASA for those operations [12] (174B (d) (ii) & 175A (d) (2)). Thus commercial operation of piston aeroplanes under night VFR and IFR is prohibited.

The ASETPA requirement defines a safety distance similar to the risk period suggested by EASA. The ASETPA safety distance is the maximum still air distance travelled in 15 minutes at the aeroplane's normal still air cruise speed plus the distance to glide to a 1000 feet above ground level (AGL) over a suitable landing area. [13]

Regarding the performance limitations, CAO Section 20.7.4 [14] gives further regulations for single-engined propeller-driven aeroplanes having a maximum take-off weight not in excess of 5 700 kg in regular public transport operations. These are similar to regulations established in Section 20.7.2 [10] for multi-engined aeroplanes but for example in landing situation the landing distance required shall be multiplied with a value of 1.43.

2.2 Risk Factors

This section aims to examine the risk factors, which are related to commercial operation of a small aeroplane in general. These factors should to be taken into account in the flight planning process while estimating the overall risk level of individual flight operation. The risk factors are categorised to four different groups, which will be further utilised and quantified in the risk assessments carried out in Section 4.

2.2.1 Aircraft

Performance class B aeroplanes are defined as propeller driven aeroplanes. Although there's no evidence that turboprop engines would be less reliable than jet engines because of their similar technology, piston engines have often been considered to be less reliable because of their greater number of moving parts. There are also differences in the redundancy levels of these engine types. Turbine engines are often more sophisticated with more intelligence and self-diagnostics. All the critical subsystems are at least doubled and performance limitation exceedances are continually monitored using automatic trend monitoring systems.

Besides the engine type, the number of engines has an impact to the risk level. One can easily say that the second engine doubles the safety but this is a misleading perception as most light twins may lose up to 80 % of their thrust if one engine fails. Thus there might not be enough power to hold the altitude or fly safely with only one engine. However, this is totally dependent of the performance of the aeroplane model in question. A problematic issue is also the different flight profile of the twin-engined aeroplanes. Because of the second engine, these aeroplanes usually have higher airspeeds, higher service ceiling, increased fuel load, and a tendency for aeroplane to yaw in an engine failure situation. [15]

Depending of the aeroplane model, some performance class B aeroplanes may have a pressurisation system, which affects to cruise altitudes. These aeroplanes are able to fly higher but there's also a risk of pressurisation failure, which can make the crew and passengers unconscious. On the other hand, a higher cruise altitude gives a pilot more time to locate a landing site in the case of power loss.

An important factor is also the redundancy of avionics installed to the aeroplane. Although all the regulation structures, part of which was briefly covered in the previous section, require backup instruments in case of electrical power faults, these backup instruments rarely cover all the functions of the original units. Especially if engine failure occurs in a single-engined aeroplane, the avionics have to rely solely on battery power as the engine is the only source of continuous electrical power. In order that enough power is left for landing gears and high lift devices, some nonessential devices must be switched off. Thus, the situation awareness of the pilot may deteriorate and this consequently increases the risk of an accident.

2.2.2 Environment

According to earlier studies, about two-thirds of all general aviation (GA) accidents that occur in instrument meteorological conditions are fatal, a rate that is three times higher than the fatality rate of all GA accidents [16]. Poor visibility, which can be a result of e.g. low cloud ceilings, fog, rain or snow, complicates the determination of the true aeroplane's position in respect to altitude and location especially under approach and landing situation. Night operations in IMC make the situation even more challenging. In addition, thunderstorms cause severe turbulence, which alone can cause the aeroplane to fall down if proper forecasts have not been obtained.

The following figures illustrate the effect of weather and lighting conditions to the risk of unsuccessful forced landing following an engine failure on a single-engined turbine aeroplane.

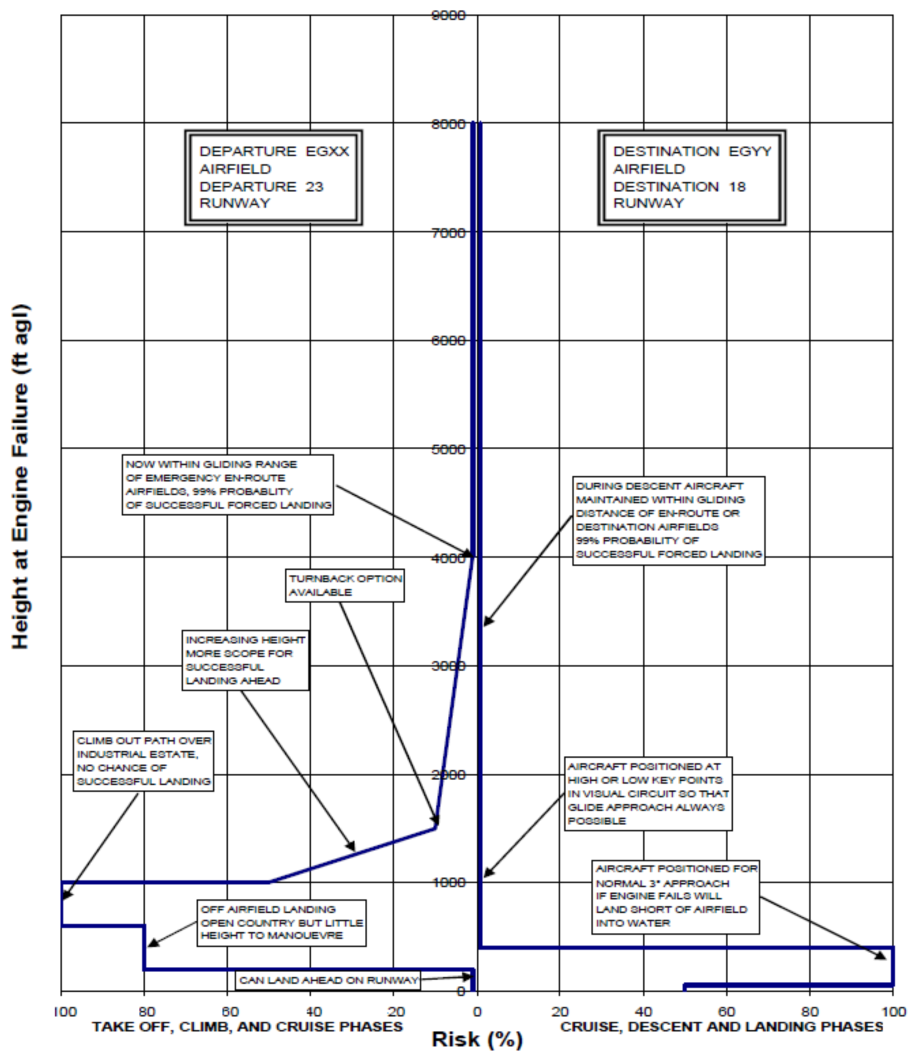


Figure 2. A risk profile example for day VMC. [6]

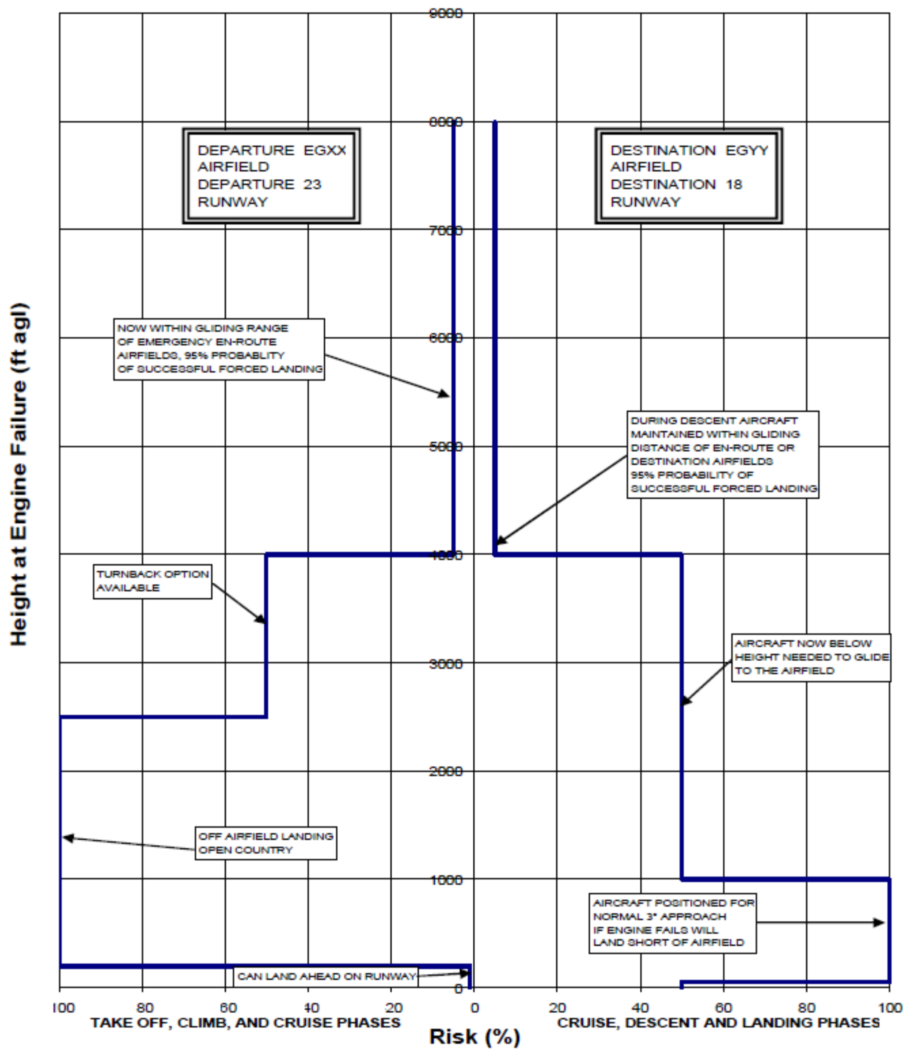


Figure 3. A risk profile example for night IMC. [6]

As Figure 2 and Figure 3 show, poor visibility reduces the available time for visual contact with runway threshold and thus increases the risk for unsuccessful forced landing. In addition, strong windshear makes the azimuth corrections harder and steers the aeroplane off the right glideslope because of its rapid change in speed and direction and a loss of lift in certain conditions [17]. This can lead to aeroplane's collision with a terrain and in this case fatal injuries to crew and passengers are likely.

In case of icing conditions, there's also a risk for freezing of windshield or flight control surfaces if anti-icing/de-icing is not working properly after engine malfunction. In such case, besides the deteriorated situational awareness, there's a serious risk that the aeroplane rapidly develops unacceptable flying characteristics. Also the performance may become degraded to the point where the assumed gliding range becomes unachievable.

In addition to hail storms, bird strikes and volcanic ash are also placed under environment category. Common to all of these are that they can seriously damage engines and therefore can lead to loss of thrust. Furthermore, hail storms and bird strikes can shatter the windshield, radar canopy and flight surfaces. These occur more often at low altitudes during take-off and approach phases. Volcanic ash on the other hand can accumulate at higher altitudes in clouds. The ash particles are often so small that they do not show up on aeroplanes' weather radars or air traffic control's radars. If the ash encounter is severe, the ash can cause major corrosion to exposed surfaces.

2.2.3 Sector

Essential in the risk assessment is also the route to be flown. It's more risky to fly over an ocean or mountains than over a flat surface with a plenty of aerodromes and open fields in the range. As previously noted, regulations limit the distance how far an aeroplane can fly from adequate aerodrome. In case of single-engined aerodromes, the 15 minutes risk period per flight suggested by EASA gives some flexibility for operators [4]. However, it can be problematic if an operator wants to extend the risk period by intermediate landings. In this way the operator gets every time another 15 minutes to be used for the next leg. It can be easily concluded that it's less risky to fly straight to the desired location than having stopovers during journey because in light of statistics, take-off and landing are the most risky part of a flight.

When considering the aerodromes, properties such as runway length, runway condition, brightness and the amount of runway lighting equipment, adequacy of navigation aids, air traffic control facilities and the level of firefighting and rescue services affect the safety of the flight. In today's world, also the level of security in the aerodromes has an effect on aviation safety by preventing illegal acts during flights.

2.2.4 Flight Crew

Factors like pilot error and crew inexperience combined with other previously mentioned factors constitute the greatest percentage of accident causes. Other indirect sources of human error are the mistakes made e.g. in maintenance and air traffic control. If the crew is not appropriately trained, it might have difficulties to correctly identify abnormal situations and follow correct standard operating procedures before the situation changes to an emergency. Cold weather operations also require expertise from the crew by correctly using de-icing fluids and on-board anti-icing/de-icing equipment in order to prevent accumulation of ice on the aeroplane's wings and fuselage.

Long exposition to heavy mental workloads causes stress that can lead to fatigue and deterioration in work performance. Under stressful conditions, diminished performance may cause unsafe behaviour and generate errors that may result in fatal accidents. [17] In addition to medical related incapacitation, the pilot might become incapacitated by subtle incapacitation, which refers to progressive degradation of a pilot's cognitive skills and capability due to fatigue.

There has also been some evidence that the age of the pilot creates a risk factor as aging is usually associated with diminished cognitive functions. However, the elevated risk has been reported rather modest or negligible with advancing age when comparing 60 year-old aviators and older with a reference group of pilots consisting of the ages of 30-39 years. [15] Instead, flight experience, as measured by total flight time at baseline, has showed a significant protective effect against the risk of crash involvement [18].

Many aviation authorities have recently begun to emphasise the importance of crew resource management (CRM). It was developed to create greater awareness of human error, identification methods and mitigation strategies. Also, in the case of fatigue, the aim is to teach employees to recognize the human factors and the resulting error trajectories in good time, and to try to avoid them and their consequences. [1] It is up to the organisation how well the CRM has been adopted as part of the organisation culture.

3 Scientific Approach to Risk Analysing Methods

3.1 Previous Research

In this section, different risk analysing methods are briefly introduced. These include:

- Fault and Event Tree Analysis;
- Failure Mode, Effects and Criticality Analysis;
- As Low as Reasonably Practicable Method;
- Monte Carlo Simulation;
- Bow-Tie and ARMS;
- Aviation Safety Risk Model;
- Analytical Hierarchy Process; and
- Flight Operations Risk Assessment System.

3.1.1 Fault and Event Tree Analysis

The often used risk diagnostics tools in aviation have been different variations of Fault Tree Analysis (FTA) and Event Tree Analysis (ETA). These can be classified as rather reactive analysis tools as they rely heavily on existing accident statistics data in the evaluation of the risk. They have been extensively utilized for example by FAA [19] and EASA [4] in their rulemaking processes. The methods are based on the utilisation of Boolean algebra to combine individual risks, which in result can cause an accident to happen.

Fault tree and event tree analysis are similar and often complimentary but they focus on opposite sides of an undesired event. Whereas FTA is concerned with analysing the faults, which might lead to an event, ETA is interested in stopping an event from escalating. The analyses are illustrated using Boolean diagrams with ‘AND’ or ‘OR’ gates and if they are used concurrently, the resulting diagram resembles a bow-tie (see Figure 7).

Like the name of FTA suggests, FTAs are presented in a tree format, where the starting point is the undesired event and it is set on top of the diagram. The immediate fault conditions, which have caused the top event, are set underneath. These can be further divided to any other subsequent faults until only primary failures are left. Logical ‘AND’ and ‘OR’ gates are used to illustrate the dependencies between the faults (see the left diagram in Figure 4).

ETAs are also presented in tree format but they are often presented in horizontal hierarchy, where the initiating event is set to the left and all consequential events branch progressively to the right. Each node has two options whether the consequential event has happened or not. As a result, the diagram shows multiple different combinations of sequential events as a total outcome (see the right diagram in Figure 4).

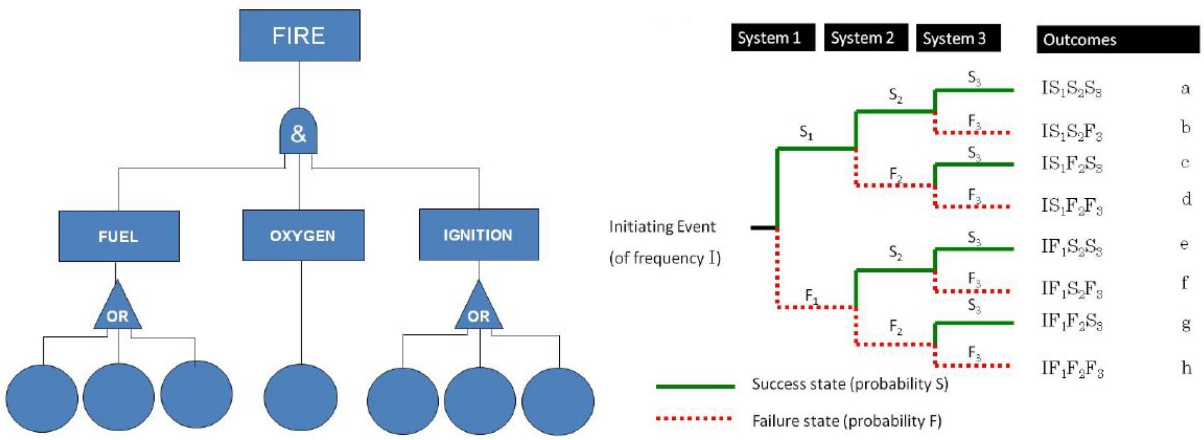


Figure 4. Basic principle of FTA (left) and ETA (right). [20]

To model aviation accidents, the faults can be depicted as risk factors, which have certain likelihood. These risk factors are either direct or indirect occurrences that have a contribution to an accident. Events on the other hand can be depicted as escalation factors, which may aggravate the initiating event.

After the risk factors are identified and their causal relationships are established, the risk factors are often quantified. A numerical probability based on either statistical data or expert judgement is established for each factor. The frequency λ is reported as occurrences per unit of time, e.g. accidents per flight hour (1/fh). The total probability P is calculated as

$$P = \lambda t, \tag{1}$$

where the parameter t is the exposure time.

To calculate the total risk, two well-established rules of combination are used for each risk factor. In the fault tree analysis, all probabilities sitting below an 'OR' gate are summed given that the probabilities are individual to each other. In turn, all probabilities sitting below an 'AND' gate are multiplied.

In event tree analysis, after the probabilities for each escalation factor are established, the final outcome probability Y_1 is achieved by following each individual track and multiplying the probabilities of the initiating event and all the factors along the track. To calculate the probability of the risk factor not happening, the complement of the probability should be used, for example $N_1 = 1 - Y_1$.

The disadvantage of FTA and ETA is that they do not take into account the severity of the consequences when quantifying risk factors. Thus a risk consisting of severe but rarely occurring factors can result in smaller risk value than the risk value resulted from negligible and frequent factors. For that reason many more profound methods have been developed.

3.1.2 Failure Mode, Effects and Criticality Analysis

From the perspective of proactive risk assessment, Failure Mode, Effects and Criticality Analysis (FMECA) was developed in the 1960s by the aerospace industry. Since then, it has been extensively used in many other industries to help ensure the safety and reliability of products. In this method, every failure mode of each system component is evaluated and their consequences to the total system behaviour are then assessed. The criticality part is used to prioritise the failures for corrective action based on the probability of the item failure mode and the severity of its effects. Without the criticality part the method is known as Failure Mode and Effects Analysis (FMEA). FMECA has been extensively applied for example by US Department of Defence in the 1980s [21]. Mathematically the equation (1) is converted to the following form

$$CN_i = \alpha_i \beta_i \lambda_p t, \tag{2}$$

in which *CN* is the criticality number, α is the failure mode and β is the failure-effect probability. This way the severity can be calculated for all failure modes of each risk factor. The combination of each factor can be then calculated in a same way as in the FTA. An alternative method called Risk Priority Number (RPN) method has also been developed but it is mostly utilised in manufacturing industries such as automotive companies. [22]

However, FMECA has often been criticised for a dilution phenomenon. For example, it is usually difficult to give precise evaluations for the variables in case there is a lack of statistical data to be used. Furthermore, different sets of the factors can produce exactly the same output value but the hidden implications may be totally different. Thus the results are strongly sensitive to variations in the criticality factor evaluations and there’s a risk that the results are not valid. For that reason, FMECA is often incorporated with fuzzy linguistic systems. [22]

3.1.3 As Low as Reasonably Practicable Method

In the risk evaluation process, one has to keep in mind that a risk can never be fully eliminated in hazardous industries like aviation. A method called As Low as Reasonably Practicable (ALARP) was formally developed in UK in the early 1990s to implement the concept of ‘goal setting’ regulations. The method defines an upper limit of risk that can be tolerated in any circumstances and a lower limit below which risk is of no practical interest as shown in Figure 5. For example, EASA has utilised the goal setting in its SET-IMC rulemaking process by establishing a target fatal accident rate of $1.3 \cdot 10^{-6}$ per flight hour [4]. In the process of establishing risk acceptance criteria, regulators have to take into account both ‘reason’ and ‘practicability’. Besides the technological aspect, also social views should be considered. [23]

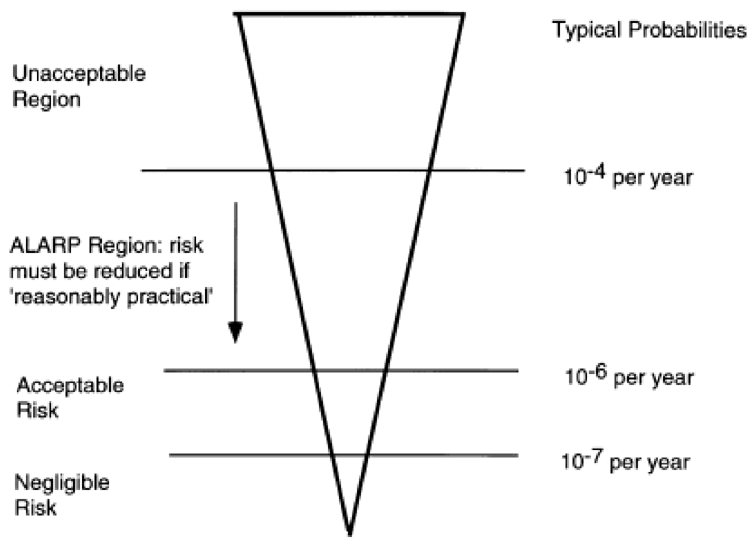


Figure 5. Example of typical levels of risk and ALARP as based on UK experience in nuclear power industry. [23]

However, some studies argue that there are a number of areas of concern about the validity of the ALARP approach. These include representativeness, morality, philosophy, political reality and practicality. An important, and in some respects fundamental, difficulty is that the risk acceptance criteria are not fully open to public scrutiny and can appear to be settled by negotiation. [23]

3.1.4 Monte Carlo Simulation

Monte Carlo simulation is a quantitative tool to simulate an accident risk by using a mathematical model of the risk scenario. It outputs a numerical risk probability value, which can be compared to ALARP target levels for example. The mathematical model is based on dynamic stochastic models of each relevant agent in the scenario. The agents represent the risk factors, which have a certain risk probability distribution. All the causal relationships and dynamic sequences between the agents are also specified in a conditional risk tree format. The model is then used to simulate the cooperation of all the agents with certain randomisers up to several thousand times to achieve a risk probability distribution for the overall risk. A graph can be generated to elicit an effect of one parameter change to overall risk (see Figure 6). [24]

The challenge of Monte Carlo simulation is that it leans heavily on quantitative data, which may not always be available or is very limited. Therefore, statistical data must often be complemented with domain expertise to estimate the probability density function for the possible values of each parameter. Furthermore, the simulation is always more or less a simplification of the risk scenario as it cannot identify all the dynamic dependencies of each risk factor and some hazards may be totally uncovered. The bias and uncertainty of the model should be carefully compared against the reality. [24]

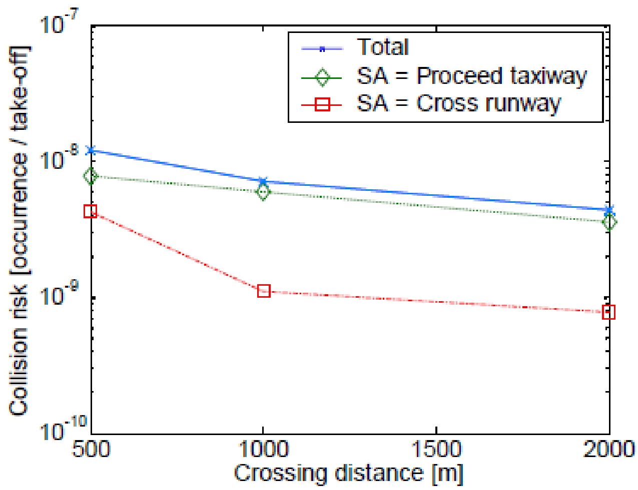


Figure 6. The collision risk for active runway crossing operation as simulated by Monte Carlo method. [24]

3.1.5 Bow-Tie and ARMS

Whereas the above mentioned methods can be categorised as rather quantitative methods, probably the two well-known and established qualitative methods in the implementation of SMS are Bow-Tie (Figure 7) and Aviation Risk Management Solutions (ARMS) (Figure 8). The methodology of Bow-Tie is simple and it has been popular since many decades. It involves systematic identification of major threats, assessment of causes (FTA) and consequences (ETA) associated to the threats and definition of specific control measures and recovery means that need to be implemented and maintained to reduce and control risks. The process is iterative and it is often developed by a team of experts and safety analysts. [25]

ARMS method is much more recent and it has been specifically developed for operational risk assessment in aviation organisations. It consists of both retrospective and prospective risk assessment, where Event Risk Classification (ERC) and Safety Issue Risk Assessment (SIRA) are the applications respectively. The first one focuses on the events that actually happened within an organisation whereas the latter generates a log for the continuous assessment of risks and control actions, through safety barriers, providing a means for safety supervision. [25]

Figure 7. Concept of Bow-Tie model. [25]

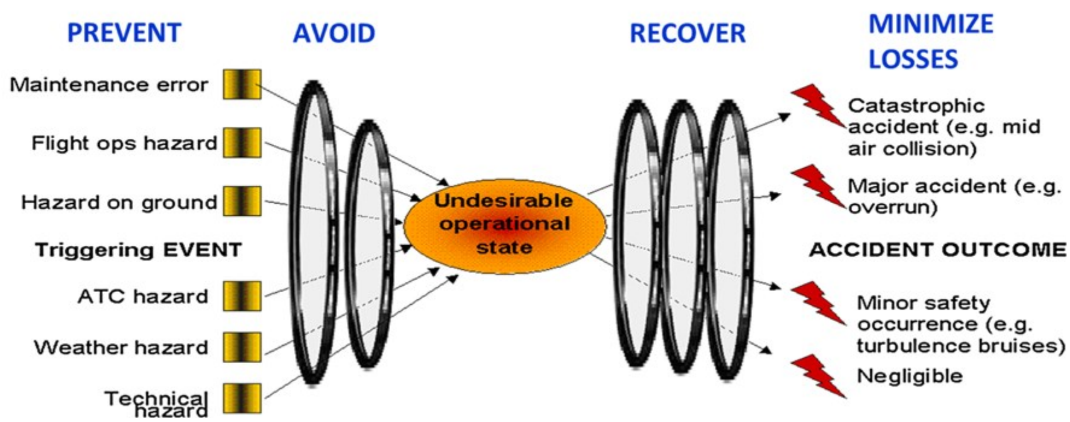


Figure 8. Safety Issue Risk Assessment of the ARMS methodology. [25]

The Bow-Tie and ARMS methods are very similar with the evaluation of causes and consequences. However, ARMS tends to lean more on the specific choice of expert judgement made by the group of safety analysts. This enables a rapid determination of risks associated to hazards that need to be assessed. This aspect on the other hand coincides with the most important drawbacks as the extensive use of expert judgement may result in the evaluation of risks that are logical but not substantially credible if epistemological aspects are not precisely followed. [25]

3.1.6 Aviation Safety Risk Model

Another useful risk analysis method is the Aviation Safety Risk Model (ASRM), which was developed with the collaboration of NASA and FAA in the early 2000s. Whereas FTA and ETA are described as inductive reasoning, this method can be described merely as deductive reasoning. It utilises Bayesian Belief Networks (BBN), which provide causal structures for aircraft accident modelling. In this application, the BBN is constructed by nodes (ovals), which represent causal risk factors or precursors in aircraft accidents, decision nodes (rectangles), which represent technology or risk intervention insertions, and arcs (arrows), which represent probabilistic causal relationships between the variables (see Figure 9). The probabilities of the causal influences between the nodes are then quantified using Conditional Probability Tables (CPT). For example, if X represents the top node (the accident scenario) and Y_1, Y_2, …, Y_n represent the parent nodes (the risk factors), the probability of the top node in the CPT can be designated as $P(X \mid Y_1, Y_2, \ldots, Y_n)$. [26]

In comparison to FTA, the conditional causalities of the risk factors and precursors in the BBNs are often estimated using “beliefs” rather than simple assumptions made using ‘AND’ or ‘OR’ gates. The strength of the belief is expressed by the numbers in the conditional probability tables. The risk mitigation effects of technologies and risk interventions are also in the form of conditional probabilities allowing the relative risk reduction to be evaluated. [26]

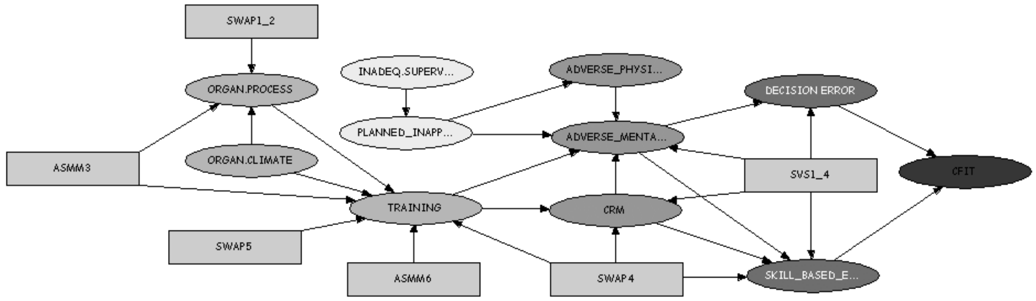


Figure 9. Example BBN for Controlled Flight into Terrain (CFIT). [26]

The models can be quantified using a mixture of accident data, if available, and expert judgement made by domain experts. However, to achieve objective results, the expert judgment must be quantified through a structured and traceable process. To model human and organisational error probabilities in the BBNs, the ASRM utilises Human Factors Analysis and Classification System (HFACS). This is a classification scheme which has been developed to capture and analyse the different types of human errors that occur. [26]

3.1.7 Analytical Hierarchy Process

Similar to ASRM is another technique called Analytical Hierarchy Process (AHP), which was first introduced in 2004. Likewise, it makes use of accident data as well as expert judgement by first obtaining the proportionate occurrence rate of causal factors from accident reports, where fatalities or serious injuries were reported and then combining this information with expert judgment on the relative importance of the flight attributes. This allows the development of importance weights for different flight characteristics in a decision process. The result is an index number used in identifying the comparative risk of flights operated under the category of general aviation. It is achieved with an equation

$$R(f) = \sum P(f_i)W(f_i), \tag{3}$$

in which $R(f)$ is the risk for a flight f associated with a particular hazard and phase of flight, f_i is the ith flight attribute (flight phase, pilot total experience, pilot recent experience, identified hazard), $P(f_i)$ is the statistical proportion of accidents with the flight attribute f_i resulting in fatality or serious injury and $W(f_i)$ is the importance weight for characteristic f_i. [27]

The flight attributes are categorised into hierarchies as presented in Figure 10. The top level of the hierarchy is the context of the investigation. On level two, there’s three broad categories and these are further refined into smaller subcategories. The proportion of each attribute’s occurrence is determined using accident databases and this is multiplied with importance weights, which are established by pairwise comparison with other flight attributes **at the same level**. The summing is made along a path from the low-level attribute up to the top level. [27]

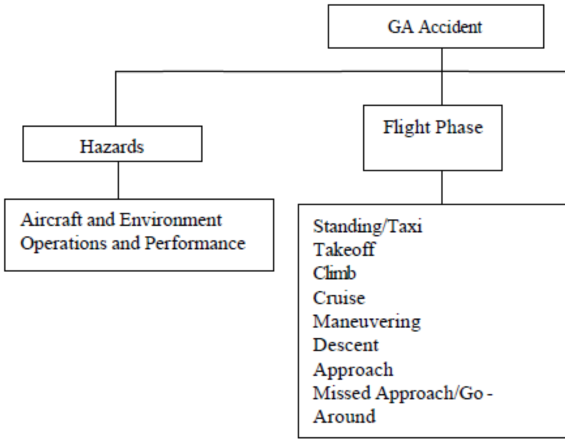


Figure 10. The AHP risk hierarchy of flight attributes. [27]

3.1.8 Flight Operations Risk Assessment System

Flight Operations Risk Assessment System (FORAS) is another indexing technique to proactively assess aviation risks. The project was originally started in 1997 by Icarus Committee, which is affiliated with the Flight Safety Foundation of USA. [28] Like the AHP, FORAS makes use of individual risk factors, which are presented as a hierarchical structure consisting of the top event (root node) and causal operation risks (child notes) (see Figure 11). The decomposition from the parent node is made until input data can be directly obtained from actual operations. [29]

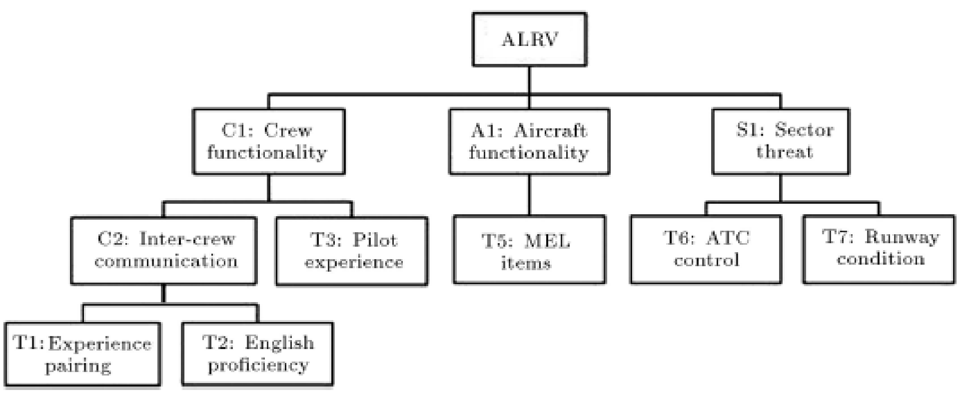


Figure 11. An example of hierarchical structure for Approach and Landing Risk Value (ALRV) used in FORAS. [29]

The distinction between the AHP and the FORAS is that the FORAS model expresses the causal relations between nodes by rules, which are assessed in a linguistic manner. Each risk and its causal risks in the FORAS model represent a fuzzy inference system. The number of rules in a fuzzy inference system depends on how many **linguistic terms** are used to assess a causal risk in each risk component. [29]

In the example of Figure 11, if two linguistic terms are used, the fuzzy inference rules can be formulated using Table 1 below. The consequence C2 is quantified by a number 1, 4, 6 or 10 depending on the states of T1 and T2. The boundaries for terms 'low' and 'high' are predetermined by using membership functions.

Table 1. A table format of fuzzy inference system when using the Sugeno system. [29]

C2:		**T2**	
		Low	High
T1	Low	1	4
	High	6	10

Often multiple rules are inferring at the same time and the combination of their consequences is calculated using weighted average with an equation

$$r = \frac{\sum_{j=1}^{m} w_j z_j c_j}{\sum_{j=1}^{m} w_j z_j}, \tag{4}$$

where r is the risk index, c_j is the membership value of jth rule's consequent, w_j is the weight of the jth rule and z_j is the firing strength of the jth rule defined by the membership functions of the antecedents. The order of the fuzzy evaluations in the hierarchy table (Figure 11) is from bottom to top. [29]

The advantage of fuzzy inference system is that it provides a natural representation of the knowledge in an expert system and automates the process of risk assessment. FORAS has already some commercial applications used by airlines for examining risk trends, assessing risks associated with each flight and quantifying the effects of making safety-related changes. The quantitative risk index allows comparisons between flights and facilitates the communication of safety issues throughout the organization. [28]

Many alternative applications utilising the fuzzy inference system have been developed. Whereas FORAS uses the *Sugeno* system that has real numbers in the consequence part [29], a risk assessment can also use the *Mamdani* system, which on the other hand adopts linguistic expressions in the consequence. This requires a separate defuzzification procedure in the inference in order to achieve quantitative results [30]. In overall, fuzzy rule-based analysis is highly adoptable and it can be modified to take input from both numerical accident data and expert judgement.

3.2 Applicable Analysing Methods

In this section, the analysing techniques considered applicable for this thesis are reviewed mathematically in an extent that their further utilisation is possible. The techniques are the weighted hierarchical model, originally introduced in Section 3.1.7, and the fuzzy rule-based analysis, originally introduced in Section 3.1.8.

3.2.1 Weighted Hierarchical Model

The first step in the process of developing a weighted hierarchical model is to determine the objective of the assessment and define the case operation. The next step is to identify all the hazards, which are related to this operation and determine their causal relationships. This forms a hierarchical tree structure as illustrated in Figure 12. At the top level, the risk factors should be the ones forming the broadest categories. These factors can be depicted as parent nodes while the objective of the assessment is the root node. Each parent node can be decomposed to more specific child notes and these can be further decomposed to smaller categories until there are only indivisible risk factors left. These nodes without any child node are called leaves. [28]

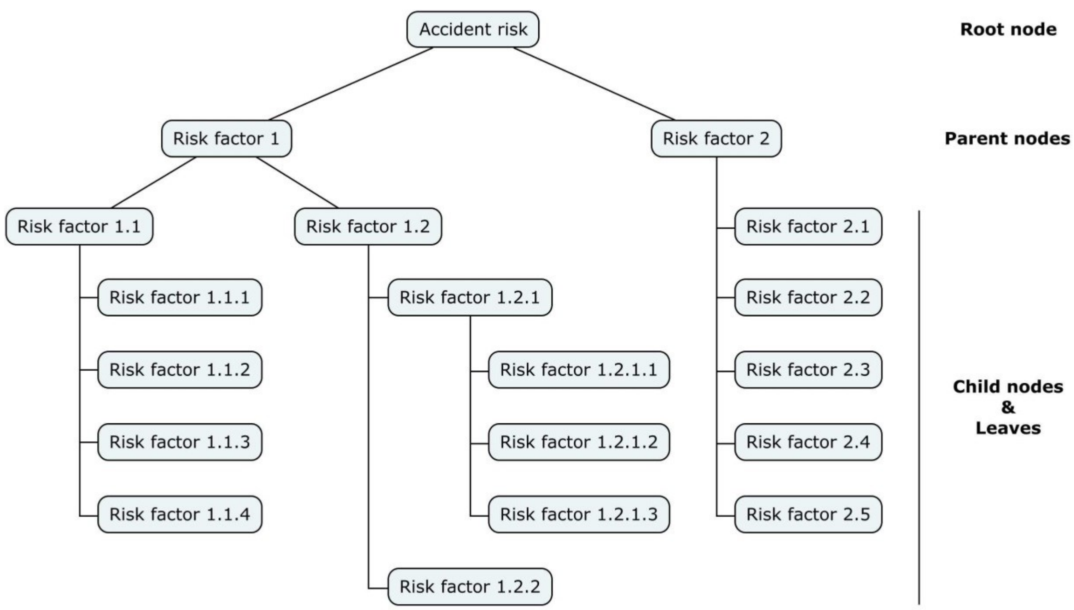


Figure 12. An example of a hierarchical model.

After the hierarchical model has been established, the weighting of the risk factors can be made by pairwise comparison. In the pairwise comparison, the experts can compare any two elements at the same level of the hierarchy in the system and provide a numerical value for the ratio of their importance. [27]

Let $x_1, x_2, \ldots, x_n$ be the set of risk factors in the same group and a_{ij} be the weight ratio of risk factors x_i and x_j, where $i = 1, 2, ..., n$ and $j = 1, 2, ..., n$. Then, the pairwise comparison can be conducted as shown in Table 2.

Table 2. Principle of pairwise comparison. [30]

	x_1	x_2	…	x_n
x_1	a_{11}	a_{12}	…	a_{1n}
x_2	a_{21}	a_{22}	…	a_{2n}
…	…	…	…	…
x_n	a_{n1}	a_{n2}	…	a_{nn}

If kept in mind that $a_{11}, a_{22}, \ldots, a_{nn} = 1$ and $a_{ji} = 1/a_{ij}$, the number of judgements N required for a group having n risk factors can be calculated using an equation [30]

$$N = \frac{n \cdot (n-1)}{2}. \tag{5}$$

Mathematically it is easiest to combine the weight ratios into a matrix $\boldsymbol{A}$ [30]:

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix}. \tag{6}$$

When developing this matrix, variables that are judged of equal importance are often assigned the value 1. A criterion that is judged to have extreme importance compared to another is often assigned the value 9. However, in different applications there are presented other possible scales as well. [30] Table 3 shows an example to determine a weight ratio by using a linguistic scale.

Table 3. A linguistic scale for a weight ratio range 1…6. [31]

Weight ratio	Description
1	Just equal (JE)
2	Almost equally important (AEI)
3	Weakly more important (WMI)
4	Strongly more important (SMI)
5	Very strongly more important (VSMI)
6	Absolutely more important (AMI)

It is also expected that each expert gives slightly different weight ratios in the pairwise comparison. In this case it is recommended to calculate a geometric mean of the given weight ratios to be inserted to the matrix. If assumed that there are m experts in the decision making process, the geometric mean can be calculated using an equation

$$a_{mean} = \sqrt[m]{a_1 \cdot a_2 \cdot \ldots \cdot a_m}, \tag{7}$$

where a_i is the importance judged by expert (ith) [27]. To determine the relative priorities of the risk factors to be used in the hierarchical model, one must calculate the eigenvector X resulting from the largest eigenvalue λ. This can be done with an equation

$$\boldsymbol{AX} = \lambda \boldsymbol{X} \leftrightarrow (\boldsymbol{A} - \lambda \boldsymbol{I})\boldsymbol{X} = 0. \tag{8}$$

However, the eigenvalues must first be solved with an equation

$$\det(\boldsymbol{A} - \lambda \boldsymbol{I}) = 0. \tag{9}$$

As a result, the method outputs n priority weights w to be used in the risk assessment:

$$\boldsymbol{X} = \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix}. \tag{10}$$

In addition, the vector should be multiplied with a multiplier $t \in \mathbb{R}$ so that each component is in its universe $\in [0, 1]$. [27] In case there are no real eigenvalues present, the eigenvalue λ should be set to unity, $\lambda = 1$ [30].

It is also possible to combine the weight ratios of all the risk factors to the same matrix regardless of their level and group. In this case the matrix gets the block diagonal matrix form and this allows simplifying the computational complexity. In this form, the matrix has a submatrix $\boldsymbol{A_{ij}}$ for each relevant group in its diagonal. If assumed that there are a total of p risk factors in the hierarchical model, the matrix gets a form

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{A_{11}} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \boldsymbol{A_{pp}} \end{bmatrix} = \begin{bmatrix} a_{11} & \cdots & a_{1n} & & \\ \vdots & \ddots & \vdots & 0 & 0 \\ a_{n1} & \cdots & a_{nn} & & \\ & 0 & & \ddots & 0 \\ & 0 & & 0 & a_{pp} \end{bmatrix}, \tag{11}$$

where a_{pp} represents the top node and equals 1 like also all the other ratios a_{ii} in the matrix diagonal. [30]

3.2.2 Fuzzy Rule-based Analysis

Fuzzy logic systems are knowledge-based or rule-based analysing tools to systematically transform human knowledge into non-linear mapping. Its fundamental speciality is that it utilises linguistic words, i.e. fuzzy sets in the assessment of overall risk. These fuzzy sets are characterised by continuous membership functions, which prescribe the boundaries for the linguistic definitions. [5] Each input and output variable has its own set of membership functions. In theory, the input and output variables can be any kind of factors having causality but in the case of safety risk assessment, the inputs are often prescribed as risk factors and the outputs as consequences. Fuzzy IF–THEN rules are then established to make a relation between consequences and a set of risk factors with a certain linguistic risk level. [28] For example, the following is a fuzzy IF–THEN rule consisting of two inputs and one output:

*IF the risk factor 1 is **low** and risk factor 2 is **average**, THEN the consequence is **moderate**.*

In the above example *low* and *average* determine the state of the output to be *moderate*. Depending on the number of fuzzy sets, a certain size of fuzzy rule base must be created to include a collection of IF–THEN rules determined by experts. [5] Based on the states of the inputs, specific rules are then retrieved form the library to determine the state of the output.

Typically the fuzzy logic system consists of four components: the fuzzy rule base, the fuzzy inference engine, the fuzzifier and the defuzzifier (see Figure 13). This configuration is called as *Mamdani* system. Without the defuzzifier, the configuration is called as *Sugeno* system. In this case the outputs are crisp numbers instead of fuzzy sets and therefore defuzzifier is not needed. [32] Basically fuzzifier/defuzzifier converts real-valued numbers to fuzzified numbers defined by fuzzy sets and vice versa. The fuzzy logic system does not limit the number of inputs and outputs but the most common configuration consists of 1-3 inputs and 1 output.

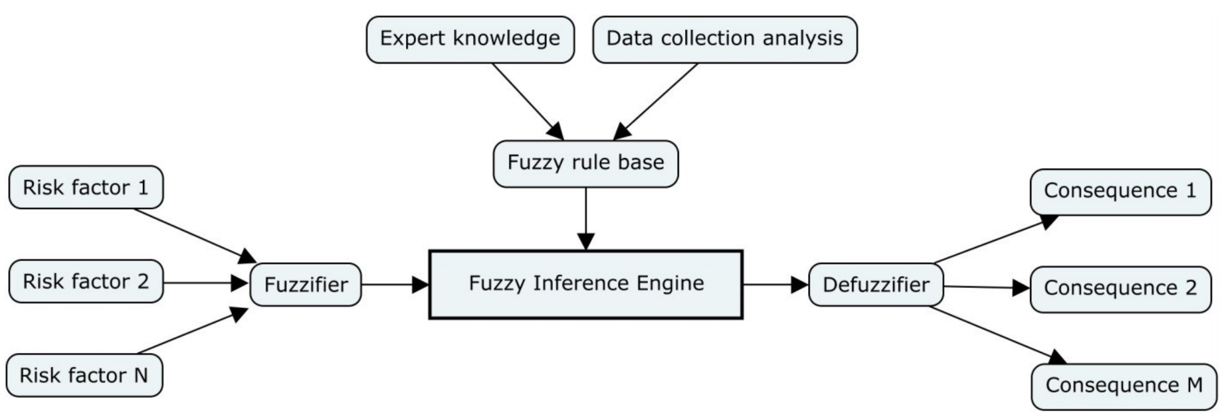


Figure 13. An overview of a fuzzy logic system.

In the next step, each of these components will be described in detail to get a better understanding of the mathematical and logical principles behind the *Mamdani* fuzzy logic system. The *Sugeno* system is distinctly similar but its membership functions in the consequent part are vertical lines (compare to Figure 14) and the output value is calculated using the equation (4).

Fuzzifier

For practical applications, the input of the fuzzy logic system is a real-valued number so it needs to be fuzzified before passing it to the fuzzy inference engine. The fuzzifier makes a mapping from a real-valued number $\boldsymbol{x^*} = (x_1^*, x_2^*, \ldots, x_N^*) \in U \in \mathbb{R}^n$ to a fuzzy set $A^j \in U$ using a membership function $\mu_{A_i^j}(x_i)$ ($i = 1, 2, \ldots, N$) of the fuzzy set [5]. x_i is in this case a component of the linguistic input variable $\boldsymbol{x} = (x_1, x_2, \ldots, x_N) \in U$. A separate set of membership functions is often defined for each input component.

In Figure 14, the terms "Very Low", "Low" etc. are the available fuzzy sets and the membership functions define their boundaries. A membership function is often a piecewise-defined triangular or trapezoidal function. For example, the triangular function has a form of

$$\mu_{A_i^j}(x_i) = \begin{cases} 0, & x_i \leq a \\ (x_i - a)/(b - a), & a \leq x_i \leq b \\ (c - x_i)/(c - b), & b \leq x_i \leq c \\ 0 & x_i \geq c \end{cases}. \tag{12}$$

However, the membership function does not have to follow the form of the equation above and it can adopt any other form as well depending on the application. In addition to triangular or trapezoidal-shaped membership functions, the function can also be Gaussian, bell or sigmoidal-shaped curve. [32]

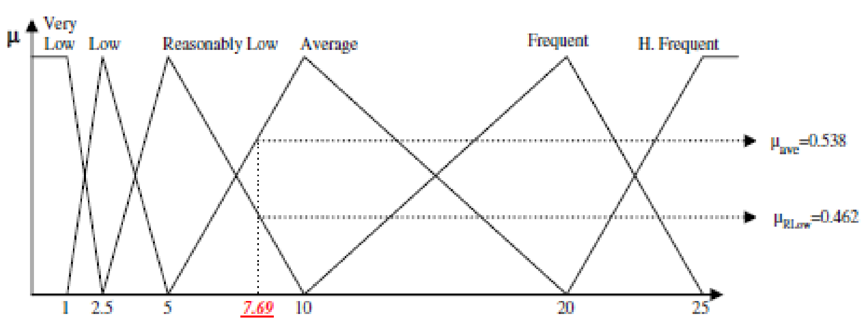


Figure 14. An example fuzzification of an input variable. [33]

Often the input value is in transition region between two fuzzy sets like in Figure 14. In this case the both fuzzy sets are taken into account in the fuzzy inference engine and they both can contribute to the output risk level of the fuzzy system with their respective weights depending on the conjunction operator [33].

Fuzzy Rule Base

The fuzzy IF–THEN rules are the core of the fuzzy logic system as they combine all the other components and determine the output of the system. In case of multiple inputs with 'AND' conjunctions in between and single output, the rules have a theoretical form

$$Ru^{(j)}: IF\ x_1\ is\ A_1^j\ AND\ \dots AND\ x_N\ is\ A_N^j, THEN\ y\ is\ B^j, \tag{13}$$

where $Ru^{(j)}$ stands for jth rule ($j = 1, 2, \dots, M$), A^j_i ($i = 1, 2, \dots, N$) and B^j are fuzzy sets in $U_i \in \mathbb{R}$ and $V \in \mathbb{R}$ respectively and $\boldsymbol{x} = (x_1, x_2, \dots, x_N) \in U$ and $y \in V$ are input and output variables of the fuzzy system. [5] The fuzzy IF–THEN rules represent human knowledge in this framework so the rule base has to fulfil the following three conditions [5] [32]:

1. The set of fuzzy IF–THEN rules has to be **complete**. This is true if for any $x \in U$, there exists at least one rule $Ru^{(j)}$ in the form of the equation (13) in the rule base so that

$$\mu_{A_i^j}(x_i) \neq 0 \tag{14}$$

   for all $i = 1, 2, \dots, N$. In other words, this means that, in any point of input space, there has to exist at least one rule in the rule base that 'fires', that is, the membership values of the input variables in the IF part has to be non-zero.

2. The set of fuzzy IF–THEN rules has to be **consistent**. This is true when there is no rules with the same IF parts but different THEN parts.

3. The set of fuzzy IF–THEN rules has to be **continuous**. This is true when there do not exist such neighbouring rules, whose THEN part fuzzy sets have empty intersection. This means that the flow from one rule to another must be fluent.

Fuzzy Inference Engine

The fuzzy inference engine is used to make a combination of multiple rules to get a mapping from a fuzzy set A^j in input space U to a fuzzy set B^j in output space V. A fuzzy IF–THEN rule can be interpreted as a fuzzy relation in the input–output product space $U\times V$. The *Mamdani's* interpretation is defined as

$$Ru^{(j)} = \int_{U\times V} \boldsymbol{\mu}_{\boldsymbol{Ru}^{(j)}}(\boldsymbol{x}, y)\, d(x, y), \tag{15}$$

where the membership function $\boldsymbol{\mu}_{\boldsymbol{Ru}^{(j)}}(\boldsymbol{x}, y)$ is a fuzzy relation of the jth rule. [32]

The firing of a set of rules via the operation composition is called *composition based inference*. In it, all rules in the fuzzy rule base are combined into a single fuzzy relation $U\times V$, which is then viewed as a single fuzzy IF–THEN rule. Thus, all the rules that have any truth in their premises will contribute to the fuzzy risk level expression.

The whole set of rules is then defined as

$$Ru = \bigcup_{j=1}^{M} Ru^{(j)}, \tag{16}$$

where the symbol ∪ is defined as a *union* operator combining the individual rules. [32]

The fuzzy relation found in the equation (15) can be calculated by implicating from antecedent to consequent. It is made with a T-norm operator [32] [33]:

$$\boldsymbol{\mu}_{\boldsymbol{Ru}^{(j)}}(\boldsymbol{x}, y) = \min(\mu_{A^j}(\boldsymbol{x}), \mu_{B^j}(y)). \tag{17}$$

Before this can be done, the inputs must be first fuzzified and a fuzzy operator must be applied to the fuzzified inputs in order to obtain one number that represents the result of the antecedent for that rule. To do this, a T-norm operator is applied to the input membership functions and $\mu_{A^j}(\boldsymbol{x})$ can be expressed as [5]

$$\mu_{A^j}(\boldsymbol{x}) = \min(\mu_{A_1^j}(x_1), \dots, \mu_{A_N^j}(x_N)). \tag{18}$$

In the equations (17) and (18), the *min* operator can be interpreted as a T-norm operator (‘AND’ conjunction) between the membership functions of two fuzzy sets. Likewise, the *max* operator is interpreted as an S-norm operator (‘OR’ conjunction).

After the fuzzy relations of each rule have been determined, the output fuzzy sets need to be aggregated so that the result is a combined single fuzzy set. The input to the aggregation process is the list of truncated output functions returned by the implication process for each rule. The output of the aggregation process is one fuzzy set for each output variable. [33] The equation (16) can be rewritten with an S-norm operator [5] [32]:

$$\boldsymbol{\mu}_{\boldsymbol{Ru}}(\boldsymbol{x}, y) = \max_{j=1}^{M}\left[\boldsymbol{\mu}_{\boldsymbol{Ru}^{(j)}}(\boldsymbol{x}, y)\right] = \max_{j=1}^{M}\left[\min(\mu_{A^j}(\boldsymbol{x}), \mu_{B^j}(y))\right]. \tag{19}$$

The output of the aggregation process is achieved with *generalised modus ponens* [5]:

$$\boldsymbol{\mu}_{\boldsymbol{B}}(y) = \sup t\big(\boldsymbol{\mu}_{\boldsymbol{A}}(\boldsymbol{x}), \boldsymbol{\mu}_{\boldsymbol{Ru}}(\boldsymbol{x}, y)\big). \tag{20}$$

Defuzzifier

Defuzzification is a process, where the fuzzy results are transformed into a precise output z^* number after the aggregated output fuzzy set is derived. It is defined as a mapping from fuzzy set $B^j \in V$ to a real-valued number $z^* \in V \in \mathbb{R}^n$. There are up to seven different methods available to do the defuzzification but the most common is the center of mass (area) method, also known as centroid method [33] [34]:

$$z^* = \frac{\int z\boldsymbol{\mu}_{\boldsymbol{B}}(y)\, dz}{\int \boldsymbol{\mu}_{\boldsymbol{B}}(y)\, dz}. \tag{21}$$

Figure 15 illustrates graphically the implication of the antecedents, the aggregation of the consequent and the defuzzification process for the case of two inputs, one output and two rules.

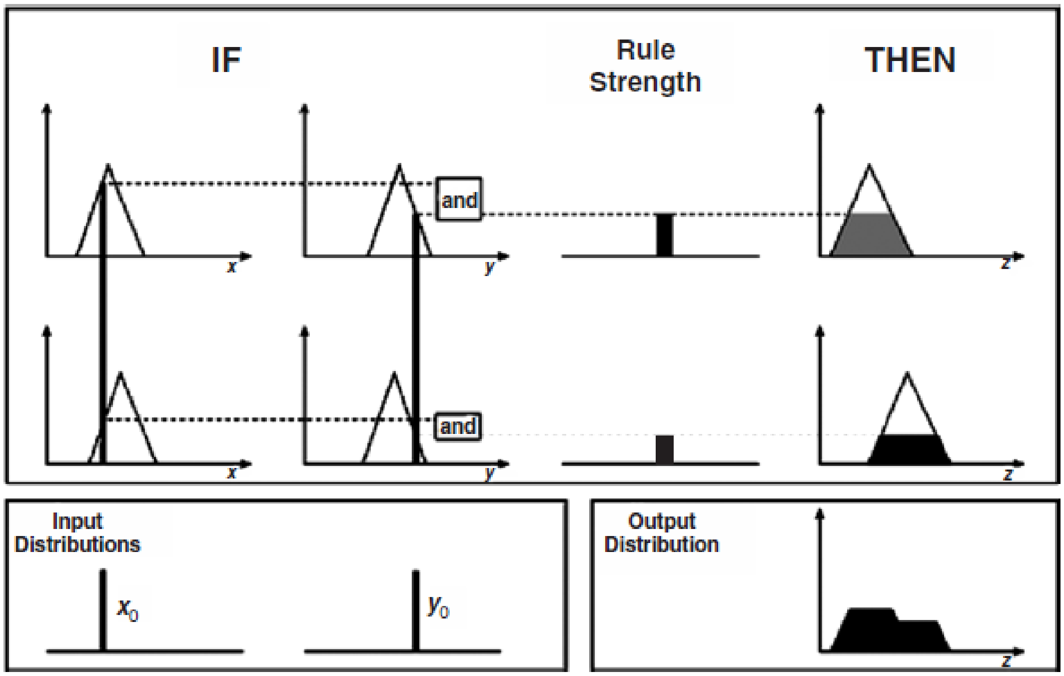


Figure 15. An example fuzzy inference system (Mamdani) with two inputs, one output and two rules. [34]

3.3 Evaluation of Analysing Methods

This section proposes a model, which will be utilised in the case examples defined in Chapter 4. The model is based on the methods described in Section 3.2. These are the weighted hierarchical analysis, i.e. analytical hierarchy process, and the fuzzy rule-based analysis. The objective is to integrate these two methods into one model so that they complement each other and that the model outputs realistic risk estimates based on expert judgement and statistics.

The resulting method is similar to AHP-FCE, which stands for analytical hierarchy process and fuzzy comprehensive evaluation. This AHP-FCE method has been originally developed in [35]. It has also been covered for example in [30], [31], [36] and [37] with slightly different variations. So far the method has been mainly utilised in the areas of body physical exercise risk, behaviour-based safety management and disaster management. Although fuzzy logic systems have been covered in the field of flight operations safety risk management to some extent, as for example in [28] and [29], they have not yet taken place as a widespread risk evaluation tool.

In the original form of AHP-FCE, the risk evaluation is conducted by building a hierarchical structure and then implementing a fuzzy transformation

$$\boldsymbol{B} = \boldsymbol{A} \oplus \boldsymbol{R} \leftrightarrow (b_1, b_2, \dots, b_n) = (a_1, a_2, \dots, a_m) \oplus \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix}, \tag{22}$$

where $b_j = \min\left(1, \sum_{i=1}^{m}\left(a_i \cdot r_{ij}\right)\right)$ (j = 1, 2, …, n). In the above equation $\boldsymbol{A}$ represents relative weight vector, $\boldsymbol{R}$ is the fuzzy relation and $\boldsymbol{B}$ is the membership degree of the remark v_j in evaluation remark vector $\boldsymbol{V} = (v_1, v_2, \dots, v_n)$. In this context, n is number of membership functions, m is number of inputs and $b_j, a_i, r_{ij} \in [0, 1]$. The evaluation is executed through the hierarchy from the bottom level to the highest and multiplying the weights vector by the fuzzy relation matrix along each segment of the path. The result is calculated using an equation

$$\boldsymbol{O} = \frac{\sum_{i=1}^{n} v_i b_i}{\sum_{i=1}^{n} b_i}, \tag{23}$$

where $\boldsymbol{O}$ is a normalized vector of the overall weights of the risk remarks. [35]

The above method has been characterised as greatly advantageous because the fuzzy environment is able to handle vague input factors and the use of hierarchical structure with a multilevel decision tree and approximate reasoning methods enables to handle complex, multi-criteria and multilevel systems. [35] However, the method does not make use of a rule base and therefore it is not as intuitive and efficient as a full fuzzy logic system. Since then, some further studies have been published with the implementation of MATLAB® and Simulink® environments, e.g. [36] [37]. With these modelling techniques many of the above mentioned limitations can be solved. The results of these studies have been promising and they encourage this thesis to further adopt and develop similar techniques.

3.3.1 Proposed Analysing Method

As a result, a risk assessment method, which is illustrated in Figure 16, is proposed to be used in this thesis for the calculation of overall risk levels.

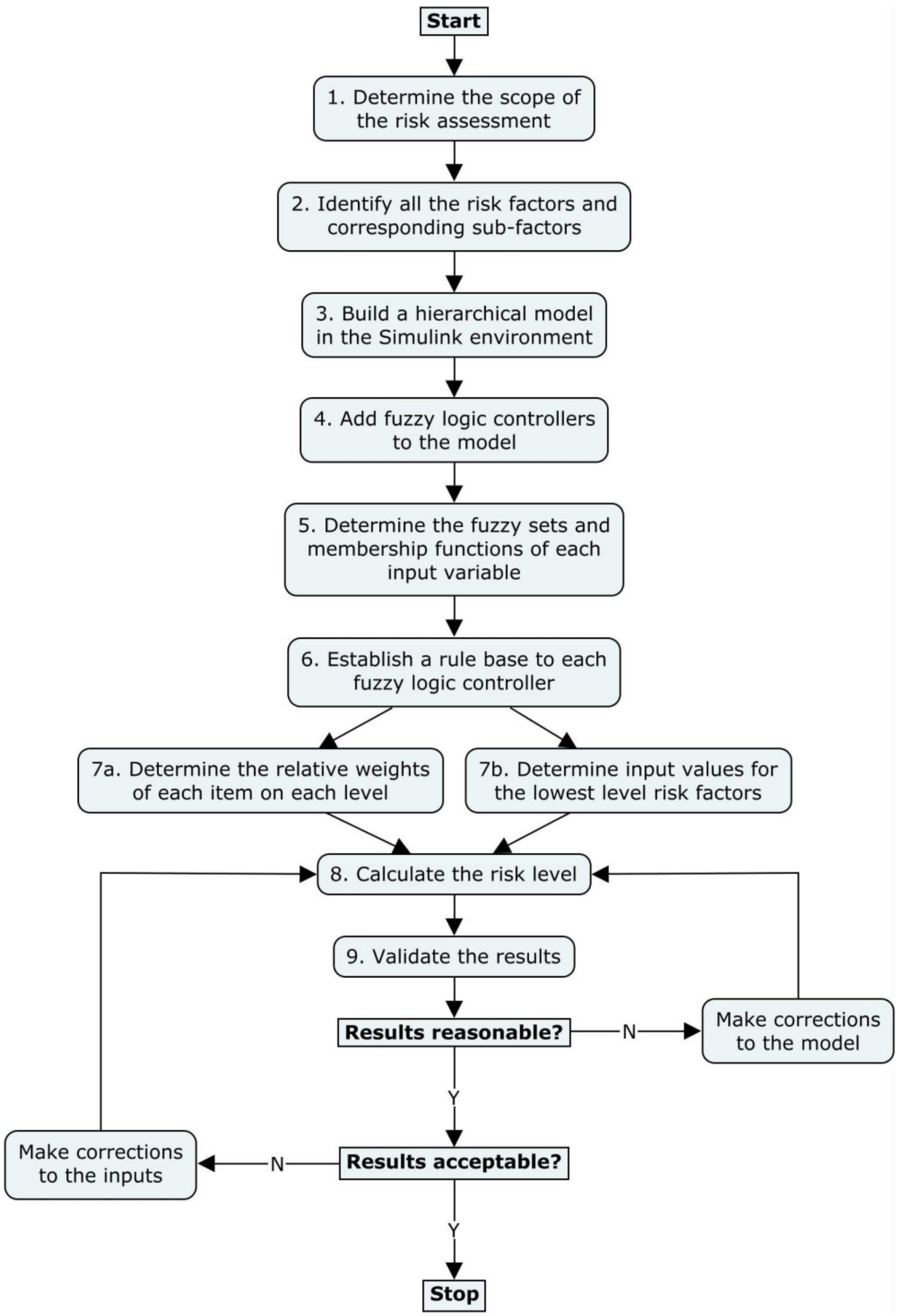


Figure 16. Schematic diagram of the proposed weighted fuzzy hierarchy method for determining a risk level.

Next, a short description of each step in Figure 16 is provided:

Step 1-2: The first step of the process is to determine the scope of the risk assessment, that is, the desired event for which the risk value is wanted to be calculated. Thereafter, all the risk factors and their subsequent subfactors related to that event should be identified.

Step 3: The next step is to build a hierarchical tree structure for the risk factors as explained in Section 3.2.1. This is done in the Simulink® environment.

Step 4-5: The fuzzy logic systems for each subsystem are built with the graphical Fuzzy Logic Designer toolbox found in MATLAB®. In this application, *Sugeno* system is preferable because of its computational simplicity. The definition of membership functions should be made by using statistics and consultation of aviation experts.

Step 6: The rule base is established by using a linear regression algorithm, which can be presented with an equation (refer also to the equation (13))

$$B^j = \frac{q-1}{Sum^M - Sum^1} \cdot \left(Sum^j - Sum^1\right) + 1, \tag{24}$$

where $B^j = 1, 2, \ldots, q$ is the fuzzy set of the output in the jth rule ($j = 1, 2, \ldots, M$) and $Sum^j = \sum_{i=1}^{N} \left(1 + \frac{10 \cdot w_i - 1}{p_i - 1} \cdot \left(A_i^j - 1\right)\right)$ is the weighted sum of the input fuzzy sets $A^j_i = 1, 2, \ldots, p_i$ ($i = 1, 2, \ldots, N$). In this context, the fuzzy sets are presented with their corresponding index numbers (e.g. 1 = low, 2 = medium, 3 = high). Compared to the AHP-FCE in the equation (22), the input weights in this case are integrated straight to the determination of risk consequents in the rule base, whereas in the AHP-FCE, the weighting is implemented in the implication phase. The method in the equation (24) is considered more effective in this case as the scaling of membership degrees downwards with weight coefficients (∈ [0, 1]) in the implication phase poses resolution problems in the output value determination phase. The justification of this algorithm is presented in Section 3.3.2.

Step 7: The relative weights and the input values of the lowest level risk factors should be determined by using expert judgement. For the calculation of the priority weight vector, a pairwise comparison procedure, explained in Section 3.2.1, should be followed. This is implemented by conducting an online survey, which is sent to multiple aviation experts. The survey enquires one by one what the importance ratio between two risk factors is in the opinion of the expert. This is repeated for all the risk factors in the same category and all the categories in the hierarchy model are reviewed this way so that the weight ratio matrices for all the categories can be formed. The final matrices used in the assessment are received after geometric mean values of all the responses have been calculated.

Step 8: The calculation process consists of the calculation of priority weights and fuzzy logic outputs on each level. A custom function is programmed in the MATLAB® environment to determine the weight coefficients from the weight ratio matrices with the eigenvector algorithm introduced in Section 3.2.1. Another function is then implemented to pick these input weights and dynamically form the rule base for each fuzzy inference controller using the algorithm presented in step 6. Thereafter, the fuzzy inference controllers in the Simulink® model can conduct the fuzzy evaluations on each level with similar methods introduced in Section 3.2.2. However, in the *Sugeno* system the min and max operators in the equations (17) - (19) are replaced with product and sum operators respectively and the equation (4) is used instead of the equation (21). However, it must be noted at this point that the rule weights presented in the equation (4) have a different meaning than the input weights used in this method. These rule weights are not used in this method and thus every rule has an equal weight of one.

Step 9: The last but very important phase is the validation of the results. The first step is to verify the operation of a single fuzzy logic block so that it gives expected output values and therefore confirm that the developed analysing method is acceptable. Thereafter, multiple runs should be conducted with different input values and the results should be compared with each other. The aim is to determine whether the results are reasonable so that the model gives realistic and consistent results. After this is confirmed, the results should be checked against the acceptable limits established for the type of operation. If necessary, appropriate risk mitigation measures should be incorporated to the model. The validation aspects are covered more in Chapter 5 and risk mitigation measures in Chapter 6.

3.3.2 Justification of the Linear Rule Base

The main function of the equation (24) is to calculate the sum of each input's fuzzy set and determine the risk consequent based on it. The indexes of the fuzzy sets are arranged so that the risk increases as the index gets larger so as a result, the risk consequent is a linear function of the risk antecedents' sum.

The rules are built systematically by going through all the possible combinations of each input's fuzzy sets from smallest to largest. The consequents are adjusted so that the smallest sum of the fuzzy sets equals one and the largest sum equals q. The intermediate sums are interpolated between these two values. The number of rules is a product of each input's number of fuzzy sets. If considered two inputs with two fuzzy sets each, the rule base has a structure as shown below:

$$IF\ x_1 = \begin{Bmatrix} 1 \\ 1 \\ 2 \\ 2 \end{Bmatrix}\ AND\ x_2 = \begin{Bmatrix} 1 \\ 2 \\ 1 \\ 2 \end{Bmatrix}, THEN\ y = \begin{Bmatrix} 1 \\ \vdots \\ \vdots \\ q \end{Bmatrix}. \tag{25}$$

By using this kind of systematic rule formation, the first two conditions on page 27 are fulfilled, i.e., the rule base is **complete** and **consistent**. However, as the method uses *Sugeno* based fuzzy inference system, the third condition is not directly applicable as only discrete numbers are used in the THEN part instead of fuzzy sets. Anyhow, the rule base is also automatically **continuous** as the consequents of all the rules with varying truth values are combined with the weighted average method, which always ensures the continuity of the output.

As the equation (24) shows, each sum element, i.e., each input's fuzzy set index is scaled based on the input's total number of fuzzy sets and priority weight. This is done in order to normalise the results based on the varying total number of the fuzzy sets (some inputs may have more fuzzy sets to describe them and therefore this would artificially have more weight to the results) and then to adjust the results based on the priority weights acquired from the pairwise comparison. A usage example of the equation (24) is presented in Table 9 on page 52. Further validation aspects of this method are presented in Section 5.1.

4 Utilisation of Model-based Risk Analysis

4.1 Creating a Risk Model

This section defines the scopes of the case examples and determines the causality of the risk factors related to these examples as in step 1-2 of the flowchart in Figure 16. The case examples are an aerodrome and landing site determination case and a flight planning case. The risk factors are then structured to a hierarchical model as in step 3 of the flowchart. The general risk factors presented in Section 2.2 are utilised throughout the process.

4.1.1 Aerodrome and Landing Site Determination

Scope

The scope of this case example is to determine the means to estimate the suitability of an aerodrome or landing site to be used either as a departure, en-route alternate or arrival point. The assessment is made by taking into account all the prevailing conditions of the flight and based on these, compute a numeric risk value for the aerodrome or landing site. The previously introduced fuzzy analysing method will be utilised for this case.

As many statistics show, the departure and arrival constitute the largest risk proportion of a flight. When choosing aerodromes for take-off and landing, the properties and equipment of the aerodromes as well as the prevailing environment conditions form the riskiness of these flight phases. Aviation authorities have therefore established numerous risk mitigation measures to reduce accidents during departures and arrivals. As already briefly introduced in Section 2.1, these include, for example, runway length requirements. Furthermore, there are also provisions for weather minimums, which depend on, e.g., location of the aerodrome and installed approach systems. Operators are also obligated to conduct an aerodrome categorisation process based on these aerodrome parameters (AMC1 ORO.FC.105(b)(2);(c)). The airport category definitions are straight from EASA requirements, which classify aerodromes either as a class A, B or C. This classification takes into account for example approach procedures and performance limitations of the aerodrome as well as any other local specialities including unusual weather conditions, obstructions, physical layout, approach lighting systems etc. [7].

For SET aeroplanes, the suggested AMC1 SPA.SET-IMC.105(d)(2) requires that the operator establishes criteria for the assessment of each new route. This includes the identification and assessment of the continued acceptability of landing sites (obstacles, dimensions of the landing area, type of the surface, slope, etc.) along the route when no aerodrome is available. [4] [6] However, conducting a rationale assessment may be challenging as multiple risk factors need to be taken into account on different importance levels. Furthermore, it may be difficult to ensure the continued validity of the assessment results as the chosen landing sites are often uncontrolled fields and possible modifications (new buildings, ditches, etc.) need to be detected by the operators themselves. Although this is not required for twin-engined performance class B aeroplanes, the en-route landing site determination would be useful especially for aeroplanes with a very little power reserve in OEI situation.

As a result, the fuzzy logic method suits well for the determination of aerodrome and landing site risk levels. The weighted hierarchical fuzzy structure can take into account all the aerodrome and landing site parameters as well as the environmental aspects, which all affect to the likelihood of successful landing. In addition, the weighting enables to emphasise certain factors over others so that the fuzzy rules output more rationale results. The operators could therefore make use of this method to comply with the EASA requirements for aerodrome categorisation and landing site determination. Also the operators of small twin-engined aeroplanes could utilise the landing site determination method to improve their safety management system although EASA's regulations do not demand the establishment of en-route landing sites (see Section 2.1.1).

Risk identification

The model for aerodrome and landing site determination consists of aerodrome and landing site risks, which are amended with risks related to prevailing environment aspects (see Figure 17). This is because, with certain environmental conditions, the risk for an unsuccessful landing (or take-off) may become too excessive although the aerodrome or landing site itself can be suitable in better conditions. As a result, the assessment is advised to be reproduced with many different environment risk combinations. The model is constructed so that, depending on the type of the location, either the aerodrome risk or landing site risk branch is chosen.

The aerodrome risk node consists of airport category and subsequent risks related to runway performance. If the airport category has not been already predetermined, the model enables its simplified determination by using the main antecedents incorporated from AMC1 ORO.FC.105(b)(2);(c). Otherwise the category value can be directly placed to the airport category node. The runway condition risk node consists of either the ratio between actual take-off run required versus take-off run available or landing distance required versus landing distance available depending on which is applicable at that point. Furthermore, it includes the effective braking action, which is directly proportional to the friction coefficient of the runway.

The landing site branch on the other hand consists of condition and dimension risks. At this point the landing site is assumed to be a plain field or road etc. The condition risk includes the information about the obstacles (tall masts near the landing site etc.), surface (grass, gravel, asphalt etc.) and the landing site elevation. Dimension risk in turn takes into account the length, width and slope of the landing area.

The environment branch in turn includes risks related to weather, lighting condition (amount of daylight) and forecasted severity of icing (low, medium, severe). The weather risk node is further modelled to be composed of runway visual range (RVR), which is proportional to reported visibility, intensity of precipitation (rain, snow fall etc.) and wind. In addition to wind speed, one must take into account also the direction of the wind and the intensity of gusts. The gust is defined as peak wind speed minus steady wind speed.

Hierarchical model

The figure below illustrates the hierarchical structure of the identified risk factors. The complete Simulink model of this aerodrome and landing site determination structure can be seen in Appendix 1.

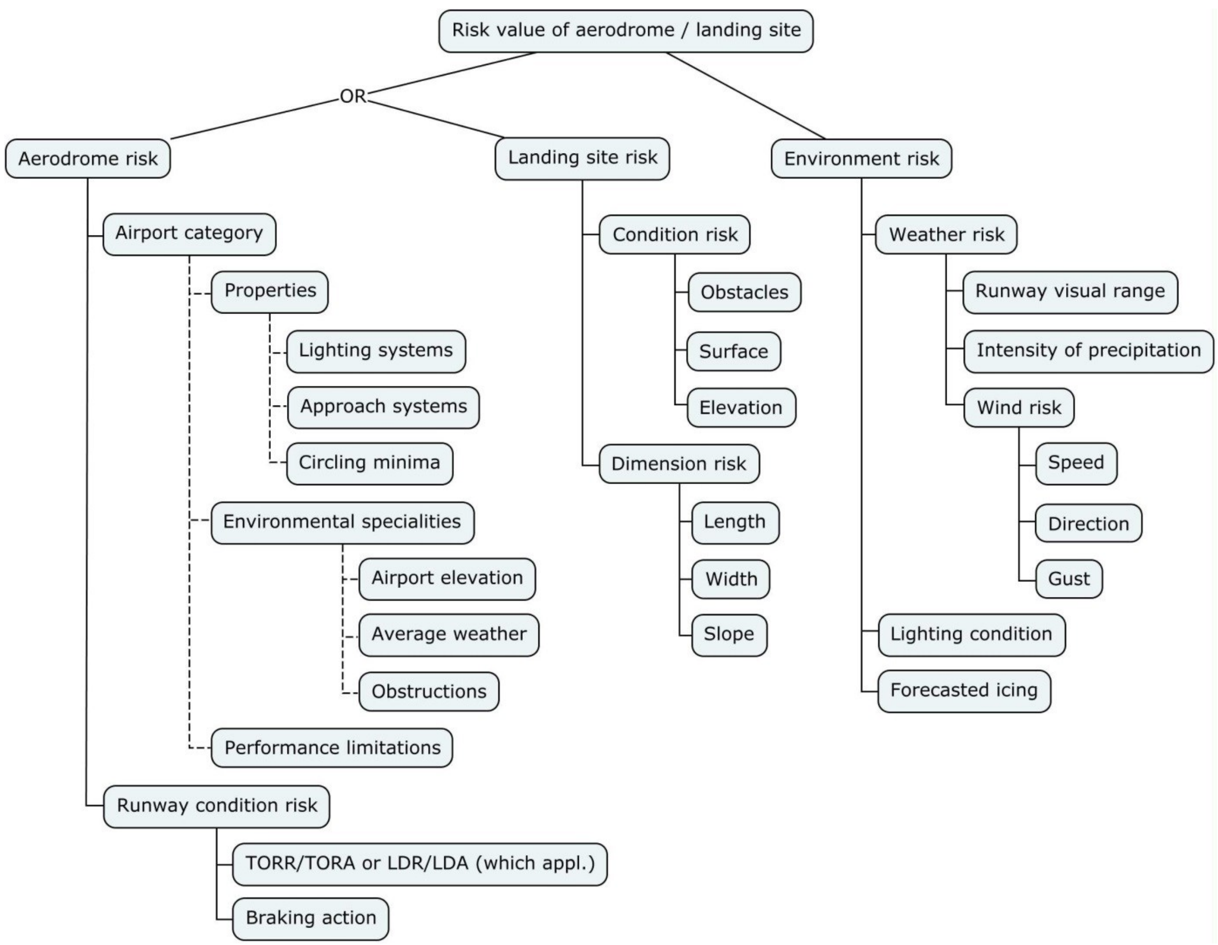


Figure 17. The hierarchical structure for the aerodrome and landing site model.

4.1.2 Flight Planning

Scope

The scope of this case example is to realistically quantify the overall risk related to an individual flight operation of performance class B aeroplane. The aim is to determine how certain selections made in the flight planning phase affect the risk. Of special interest are parameters such as the number of engines and the engine type of the operated aeroplane. As in Section 2.1.2, many aviation authorities do not either permit the commercial operation of single-engined turbine aeroplanes in IMC or at night or they have established additional requirements to this kind of operations as they believe that these operations contain a higher risk.

Especially EASA has emphasised the importance of proper route planning in the flight preparation phase. The agency believes that by reducing the time of risk period in a flight, the fatal accident risk can be greatly reduced. EASA has also established a numeric method in GM2 SPA.SET-IMC.105(d)(2) proposed to be utilised by operators in order to verify that the amount of in-flight risk does not exceed certain limits [4] [6]. However, this method does not take into account other sources of risks and it's highly sensitive to subjective judgement made by the operators.

The fuzzy rule-based model developed for this case example aims to provide an alternative and more precise tool to be used by operators. As earlier mentioned, the 'fuzzy' environment provides an advanced platform to handle imprecise and ambiguous judgements. This is necessary as reactive interpreting of accident statistics alone is inappropriate. Furthermore, this method incorporates other risk sources as well to complement the route based risks and weights their consequences appropriately. The output will be a crisp, comparative risk value for each flight. The objective is that this method can be utilised for the operation of both single-engined as well as two-engined aeroplanes.

Risk identification

The planned flight primarily includes sector-based risk factors, which can be divided to risks encountered during departure, en-route and arrival phases of flight (see Figure 18). The departure and arrival risks are directly calculated using the risk model for aerodrome determination described previously. The en-route risk on the other hand is a combination of risk period usage, planned cruise altitude and the risk value for en-route alternates. To be conservative, the value for the last one is determined by finding the largest risk value of all the planned en-route alternates. The calculation of alternates is also done with the model in the previous section so that only the applicable branch of the model is chosen.

Moreover, the overall risk for a planned flight also depends largely on the flight crew and the operated aircraft. For that reason, the sector risk branch has been amended with a parallel flight crew risk and aircraft risk branches. Depending on their values, the combined risk value may become excessive with certain routes and thus some risks have to be mitigated in one of these areas.

The flight crew branch is assumed to consist of pilot error and incapacitation risks. The pilot error risk is largely proportional to flight crew's experience and training as well as their fatigue level. The experience can be readily described with the captain's and co-pilot's accumulated total, type-specific and recent flight hours whereas training level is measured by estimating the performance of crew resource management (CRM) and standard operating procedures (SOP). The fatigue level in turn can be derived from the duty hours and the number of previous sectors in the duty period. However, the incapacitation risk is much more difficult to be modelled as a risk for a serious acute medical issue during a flight can be attributed to numerous different cases. For simplicity, the age of each pilot is assumed to be the main contributor for the incapacitation risk. This is also amended with the information whether one of the pilots has operational multi-crew limitations (OMLs).

The aircraft branch is decomposed to risks related to aircraft model, aircraft age and critical minimum equipment list (MEL) items. The most essential aspect of the aircraft model risk is the redundancy risk consisting of information about aircraft's climb gradient in engine inoperative situation and critical safety equipment installations (reverser and anti-skid). This is amended with the reliability risks related to propulsion (engine and propeller) and other critical systems (pressurisation and electrical power). The reliability is described using numerical failure rates acquired mostly from statistics. They can be quantified by using unit occurrences per flight hour. The aircraft age is divided into model age, which tells the novelty of the aircraft model (**not** individual aircraft's age), and the frequency of unexpected failures. The frequency of unexpected failures is considered to be a better indicator than individual aircraft age as also an old aircraft can be equally safe if it is maintained well and there's little system failures between scheduled maintenances. On the other hand the high number of active critical MEL items is considered to be a risk factor. This includes active category A and B items as well as rectification interval expiry (RIE) items, which stand for MEL items not rectified within specified time period.

Hierarchical model

The figure below illustrates the hierarchical structure of the identified risk factors. The risk factors marked with (*) are intended to be specified using the model for aerodrome and landing site determination (see Figure 17). The complete Simulink model of this flight planning structure can be seen in Appendix 2.

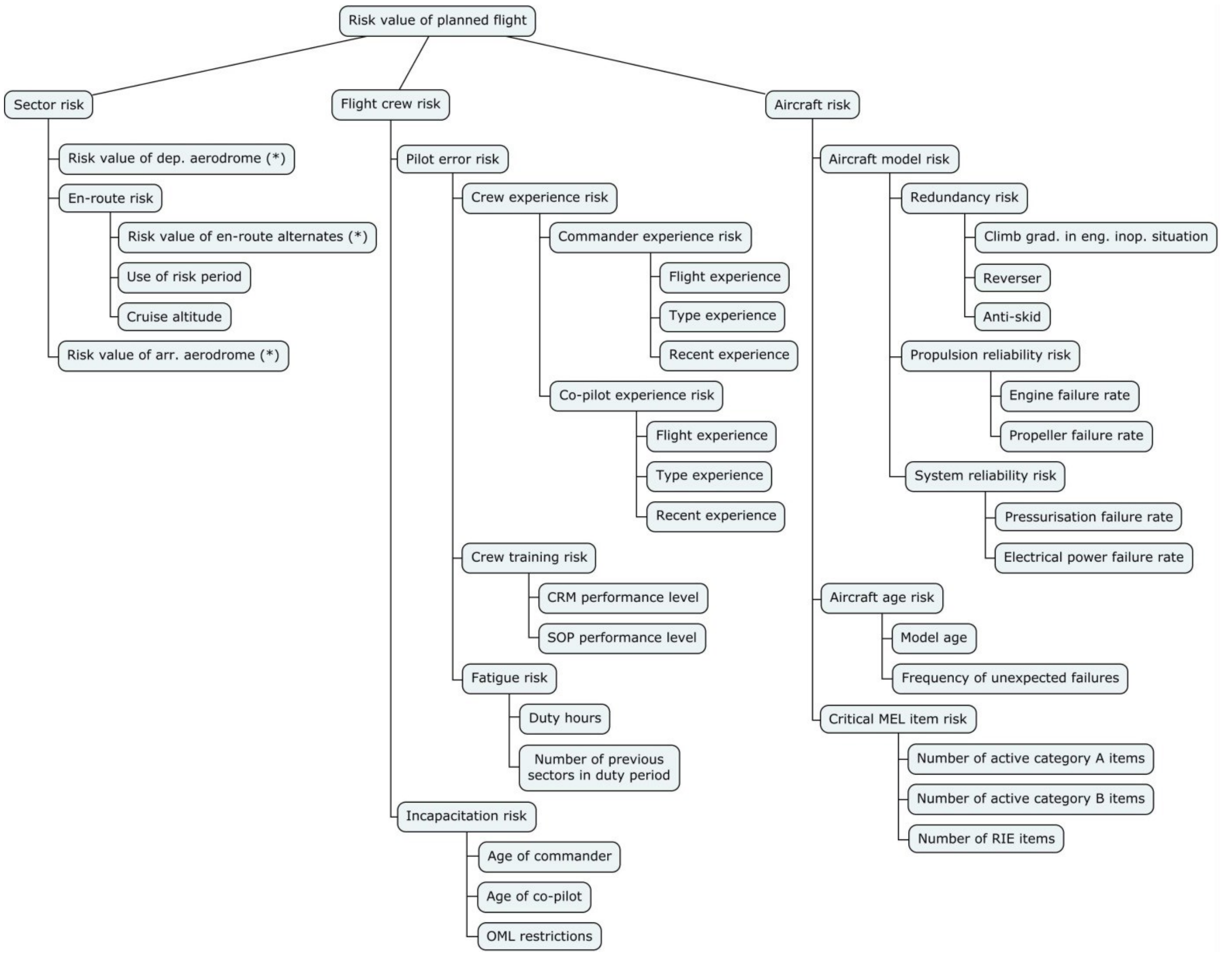


Figure 18. The hierarchical structure for the planned flight model.

4.2 Data Acquisition

4.2.1 Domain Human Expert Experience

Membership Functions

This section covers steps 4-5 of the process flowchart (Figure 16) by first introducing the fuzzy inference system (FIS) interface and then defining the membership functions to each fuzzy inference controller. These definitions were made by consulting aviation experts in CAA Finland.

The core of the modelling process is the Fuzzy Logic Designer developed for MATLAB®. The graphical user interface is illustrated in Figure 19. The main window enables defining the inputs and outputs as well as the fuzzy operators used in the calculation (refer to Section 3.2.2). It also provides access to the membership function and rule editors as well as to rule and output graph viewers. However, for effective and dynamic system modification, it is preferred to use text based .fis files in the initialisation of the fuzzy controller. This way the file can be loaded to the workspace as a structure variable, which can be modified dynamically during the execution of the risk analysis program.

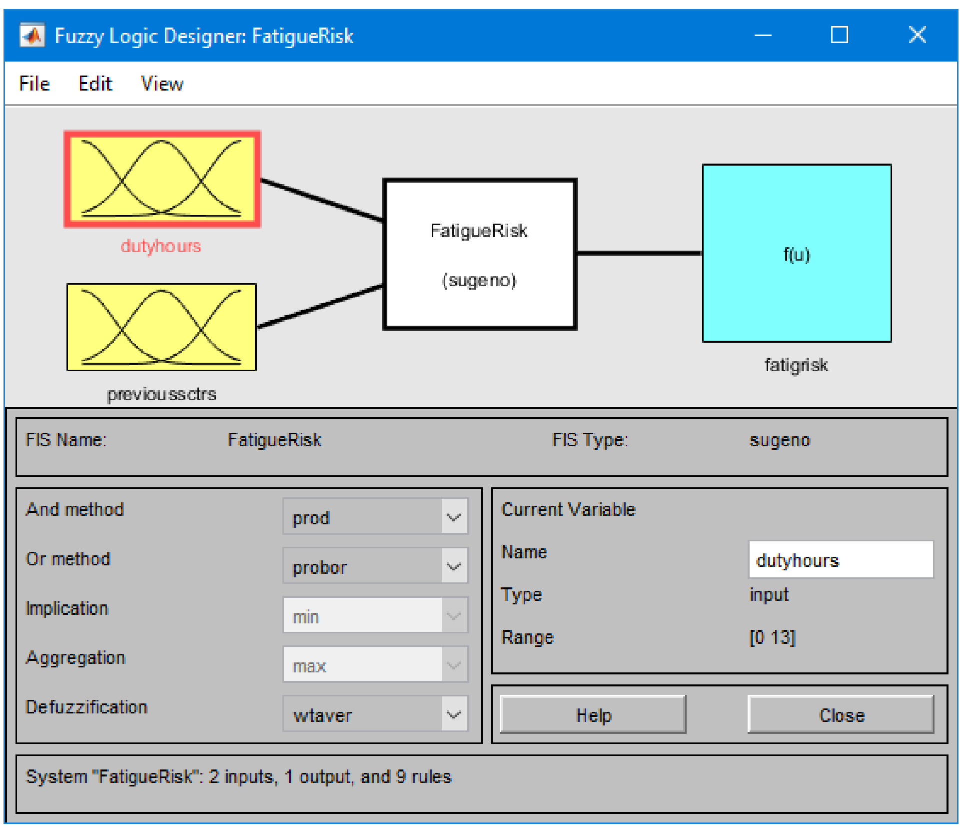


Figure 19. The graphical user interface of the Fuzzy Logic Designer. Source: MATLAB®.

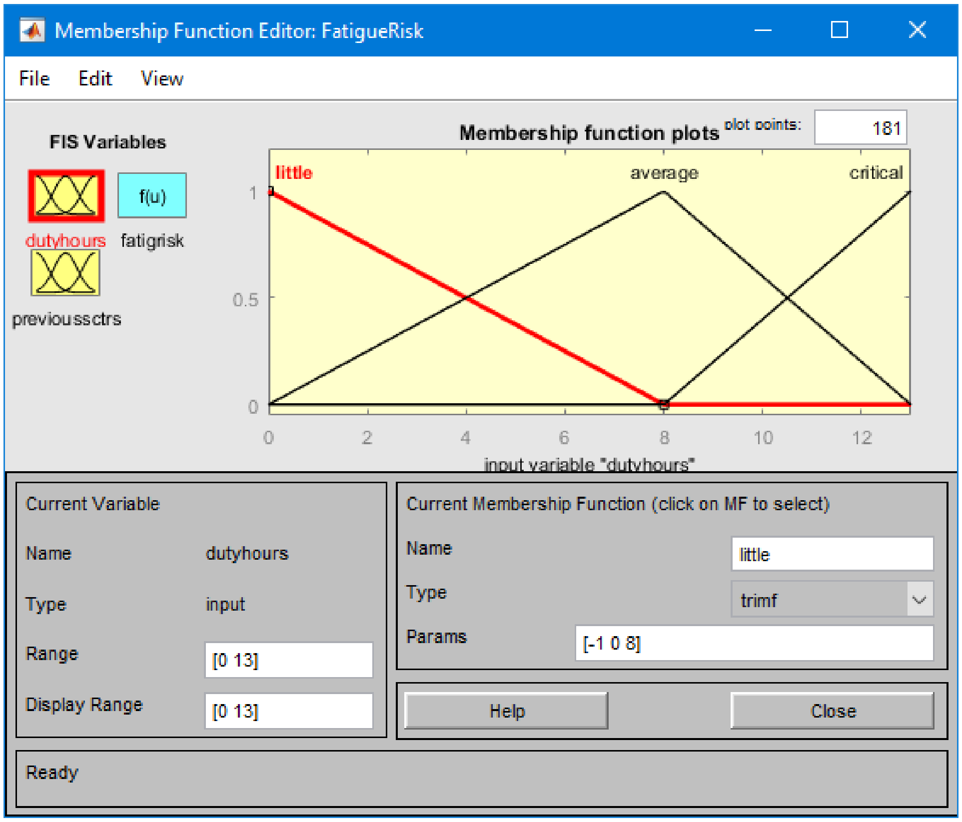


Figure 20. The definition of the membership functions. Source: MATLAB®.

The membership function editor (see Figure 20) enables defining the numerical boundaries for the fuzzy sets, which describe the state of the input variables in a linguistic manner. On the lowest hierarchy level of a risk model, the input variables of a fuzzy controller are parameters, which mostly are directly obtainable from actual operations. In Figure 20, for example, the values on the horizontal axis are hours and amount of sectors. In the definition of the input variable's permissible range, one must take into account the applicable aviation regulations. For example, the maximum permissible number of duty hours for a pilot is 13 hours without the use of extensions and assuming 1-2 sectors in the duty period (ORO.FTL.205). In case there are no maximum permissible upper limit defined by the aviation regulations (e.g. flight experience), one must consider what the maximum reasonable number is in the context of the operation's nature.

In the definition of the membership functions for the fuzzy sets, triangular-shaped functions are preferred in this thesis. In addition, the boundaries for the functions are selected so that the next membership function starts at the position, where the maximum of the previous function lies. This enables a smooth and linear risk increment (or diminishment) as a function of the input variable. In case there is no linear relation between the risk increment and input variable, trapezoidal-shaped membership functions should be used instead. For example, there is no clear evidence that risk would increase when an aircraft model age is between 10 and 15 years.

Table 4 and Table 5 show the results of the input membership function definitions for the aerodrome and landing site determination model (Figure 17) and the flight planning model (Figure 18) respectively. The definitions are sorted so that the fuzzy sets being least risky are placed to the left side whereas the most risky fuzzy sets are placed to the right side.

Some of the inputs have a continuous range and some are meant to be discrete. The continuous inputs have primarily an engineering unit, which unambiguously expresses the state of that input. However, the inputs with a discrete range do not have any unit and the user have to choose between the available alternatives. Often this information is obtainable, for example, from an aeronautical information platform (AIP) or airport flight information service (AFIS). If not, the value must be concluded by using other available means or rationale judgement.

Table 4. The definition of the input membership functions for the aerodrome and landing site determination model.

	Input code	Unit	Range	Definition of the membership function
Aerodrome risks	**light_systems**	-	1...5	FALS = 1, IALS = 2, BALS = 3, NALS = 4, no lights at all = 5
	appr_systems	-	1...4	precision = 1, APV = 2, non-precision = 3, no IFR = 4
	circling_min	ft	0-2 000	(height) normal < 1000, abnormal > 1000
	airport_elev	ft	0-15 000	low < 5000, medium 5000-8000, high > 8000
	avg_weather	-	1, 2	normal = 1, unpredictable weather, high temp etc. = 2
	obstructions	ft	0-10 000	(= MSA-aerodrome elevation) low < 3000, medium 3000-5000, high > 5000
	perf_limits	-	1...4	normal profile = 1, steep take-off profile (> 3.3%) = 2, steep approach profile (> 3°) = 3, both steep profiles = 4
	rwy_ratio	-	0-1	(= TORR/TORA or LDR/LDA) long < 0.5, medium 0.5-0.7, short > 0.7
	braking_act	-	0-0.5	good > 0.4, medium/good 0.39-0.36, medium 0.35-0.3, medium/poor 0.29-0.26, poor < 0.25
Landing site risks	**obstacles**	ft	0-10 000	(= approximated MSA-landing site elevation) low < 3000, medium 3000-5000, high > 5000
	gnd_surface	-	1, 2, 3	asphalt = 1, flat gravel/grass = 2, rugged gravel/grass = 3
	elevation	ft	0-15 000	low < 5000, medium 5000-8000, high > 8000
	length	-	0-1	(= LDR/LDA) long < 0.3, medium 0.3-0.7, short > 0.7
	width	m	0-50	wide > 45, medium 20-45, narrow < 20
	slope	º	0-10	normal < 2, abnormal 2-6, extreme > 6
Environment risks	**rvr**	-	0-5	(= RVR actual/RVR required) good > 2, medium 2-1.5, bad < 1.5
	precipitation	mm	0-15	light < 3, moderate 3-11, heavy > 11
	wnd_spd	m/s	0-30	light < 5, gentle 5-10, moderate 10-14, strong > 14
	wnd_drctn	º	0-180	head < 30, cross 30-150, tail > 150
	wnd_gust	m/s	0-30	(= gust-steady) low < 5,medium 5-15, high > 15
	light_cond	-	1, 2, 3	day = 1, twilight = 2, night = 3
	icing	-	1, 2, 3	low = 1, medium = 2, severe = 3

NOTE: The explanations for the input codes can be seen in Figure 17.

Table 5. The definition of the input membership functions for the flight planning model.

	Input code	Unit	Range	Definition of the membership function
Sector risks	**departure**	-	-	Acquired from the other risk model
	alternate	-	-	Acquired from the other risk model
	risk_period	%	0-100	low < 30, medium 30-70, high > 70 (0 for twin-engined)
	altitude	ft	5 000-3 0000	high > 20000, medium 20000-10000, low < 10000
	arrival	-	-	Acquired from the other risk model
Flight crew risks	**cmndr_total**	fh	200-12 000	high > 4000, medium 4000-1500, low < 1500
	cmndr_type	fh	12-3 000	high > 1000, medium 1000-300, low < 300
	cmndr_recent	fh	0-300	high > 50, medium 50-20, low < 20
	copilot_total	fh	200-6 000	high > 2000, medium 2000-700, low < 700
	copilot_type	fh	12-3 000	high > 1000, medium 1000-300, low < 300
	copilot_recent	fh	0-300	high > 40, medium 40-20, low < 20
	crm_perf	-	1, 2, 3	efficient = 1, satisfactory = 2, inefficient = 3
	sop_perf	-	1, 2, 3	efficient = 1, satisfactory = 2, inefficient = 3
	duty_hours	h	0-13	little < 6, average 6-10, critical > 10
	previous_sctrs	-	0-8	little < 2, medium 2-4, high > 4
	age_cmndr	-	18-70	young < 50, middle 50-60, old > 60
	age_copilot	-	18-70	young < 50, middle 50-60, old > 60
	oml_rstrctns	-	1, 2	no = 1, yes = 2
Aircraft risks	**climb_grad**	%	-20-20	good > 5, medium 5-(-8), bad < -8
	reverser	-	1, 2	equipped = 1, not equipped = 2
	antiskid	-	1, 2	equipped = 1, not equipped = 2
	eng_failure	10^{-6} 1/fh	1-10	good < 2, medium 2-6, poor > 6
	prop_failure	10^{-8} 1/fh	1-10	good < 5.5, poor > 5.5
	pres_failure	10^{-8} 1/fh	1-10	good < 5.5, poor > 5.5
	power_failure	10^{-8} 1/fh	1-10	good < 5.5, poor > 5.5
	model_age	-	0-40	middle 10-30, new < 10, old > 30
	freq_unexp	10^{-3} 1/fh	0-150	good < 25, medium 25-50, poor > 50
	num_cat_a	-	0-5	good 0, satisfactory 1-2, bad > 3
	num_cat_b	-	0-5	good 0, satisfactory 1-2, bad > 3
	num_rie	-	0-5	good 0, satisfactory 1, bad > 2

NOTE: The explanations for the input codes can be seen in Figure 18.

The membership functions of the continuous inputs are configured so that the function gets it maximum value at the center of the fuzzy set's range if the both ends are closed. If the other end is open, the function gets the maximum value at the minimum or maximum of the input depending on which is applicable. However, in some instances, where trapezoidal-shaped membership functions are used, the function gets the maximum value already at the verge of the fuzzy set's range. The membership functions of the discrete inputs in turn get their maximum at the point of the fuzzy set's range.

Weights of the Risk Factors

In this section, a closer look is taken to the step 7a in Figure 16. The priority weights were established by a pairwise comparison method introduced in Section 3.2.1. The data to the weight ratio matrices was collected by an online survey, which was sent to multiple aviation experts in CAA Finland, EASA and Hendell Aviation. In this survey, the linguistic scale shown in Table 6 was used in the process.

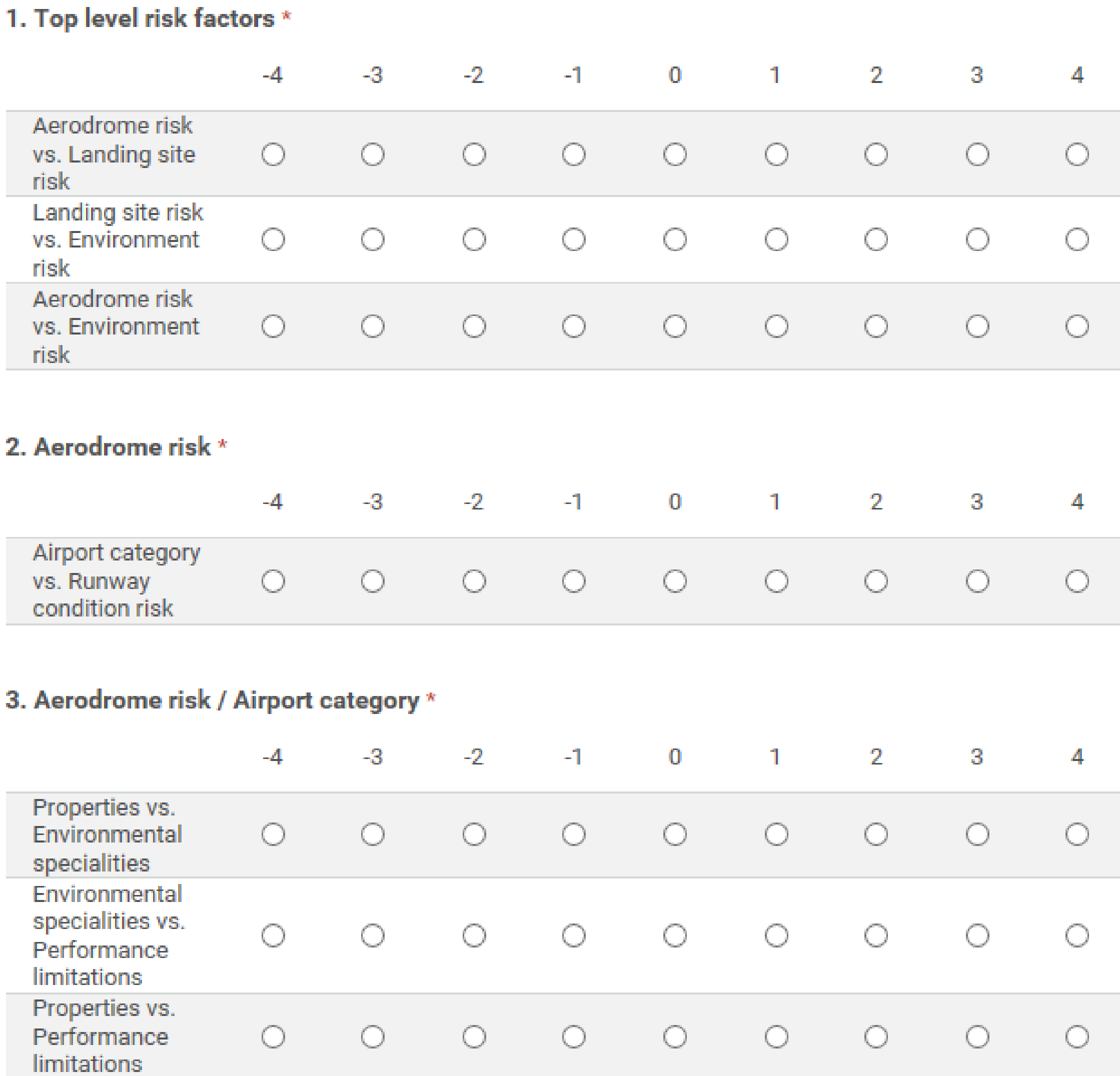
Table 6. The linguistic scale used in the online survey.

Column number	Corresponding weight ratio	Description
-4	1/5	Absolutely less important
-3	1/4	Very strongly less important
-2	1/3	Strongly less important
-1	1/2	Weakly less important
0	1	Just equal
1	2	Weakly more important
2	3	Strongly more important
3	4	Very strongly more important
4	5	Absolutely more important

A screenshot of the actual survey is presented in Figure 21. Both risk models were reviewed systematically by examining one branch at a time from top to bottom. The experts were asked to think how essential they considered the influence of a first risk factor compared to another risk factor. In other words, if they considered the first risk factor more important compared to the other and, hence, gave more ‘weight’ to it, then the value of that risk factor would have more ‘power’ to affect the output risk value of the whole risk model.

A total of nine experts answered to the survey. The majority of them were inspectors and special advisers from CAA Finland but also one response from EASA and a couple responses from Hendell Aviation were received. Many of these experts were also professional pilots.

The challenge in the filling the survey was being consistent with the answers. There were a total of 30 questions and 70 evaluations to be made, in which risk factors were compared on multiple different levels and contexts. It may have been difficult to always keep in mind in which order the risk factors were supposed to be compared and give the correct ‘weight’ accordingly. Furthermore, the answers are always strongly subjective to the opinion of each expert. These matters explain the relatively large standard deviation (76.7 %). With a larger number of participants, the deviation would probably have been smaller. However, for consistent and justified weight ratios, a single brainstorming event may have been a better alternative.


1. Top level risk factors *

	-4	-3	-2	-1	0	1	2	3	4
Aerodrome risk vs. Landing site risk	○	○	○	○	○	○	○	○	○
Landing site risk vs. Environment risk	○	○	○	○	○	○	○	○	○
Aerodrome risk vs. Environment risk	○	○	○	○	○	○	○	○	○

2. Aerodrome risk *

	-4	-3	-2	-1	0	1	2	3	4
Airport category vs. Runway condition risk	○	○	○	○	○	○	○	○	○

3. Aerodrome risk / Airport category *

	-4	-3	-2	-1	0	1	2	3	4
Properties vs. Environmental specialities	○	○	○	○	○	○	○	○	○
Environmental specialities vs. Performance limitations	○	○	○	○	○	○	○	○	○
Properties vs. Performance limitations	○	○	○	○	○	○	○	○	○

Figure 21. A screenshot of the online survey showing the first three questions.

The answers of each aviation expert were combined using geometric average (equation (7)) to get representative weight ratios. These weight ratios were then inserted to an Excel (MS Office) sheet to form the weight ratio matrices. A custom MATLAB® function, which is part of the risk assessment program, can then pick these matrices from the Excel sheet and dynamically calculate the final weight coefficients during the execution of the program. This is done with the eigenvector algorithm established in the equations (8) and (9). The function also scales the vector components so that the largest weight coefficient is one.

The full weight ratio matrices of the aerodrome and landing site determination and flight planning risk models are presented in Appendix 3 and Appendix 4 respectively. The final weight coefficients are presented in Table 7.

Table 7. The priority weights of the risk factors in Figure 17 and Figure 18 respectively.

Risk factor code	Value
aerodrome_risk	0.3785
lnd_site_risk	1
environ_risk	0.5958
airport_cat	1
rwy_cond_risk	0.7489
properties	0.8195
environ_spec	1
perf_limits	0.8195
light_systems	0.9002
appr_systems	1
circling_min	0.5482
airport_elev	0.6789
avg_weather	1
obstructions	0.9895
rwy_ratio	1
braking_act	0.8194
cond_risk	0.8194
dimen_risk	1
obstacles	1
gnd_surface	0.7434
elevation	0.4056
length	1
width	0.5971
slope	0.6036
weather_risk	1
light_cond	0.6339
icing	0.8795
rvr	1
precipitation	0.5195
wind_risk	0.6672
wnd_spd	0.6505
wnd_drctn	1
wnd_gust	0.8574

Risk factor code	Value
sector_risk	0.6608
flight_crew_risk	1
aircraft_risk	0.7434
departure	0.7489
enroute_risk	0.3843
arrival	1
alternate	1
risk_period	0.9499
altitude	0.6758
pilot_error_risk	1
incap_risk	0.3512
crew_exp_risk	0.6616
crew_tr_risk	1
fatig_risk	0.7132
cmndr_exp_risk	1
copilot_exp_risk	0.7169
cmndr_total	1
cmndr_type	1
cmndr_recent	0.9138
copilot_total	0.8482
copilot_type	0.8664
copilot_recent	1
crm_perf	1
sop_perf	0.8851
duty_hours	1
previous_sctrs	0.9871
age_cmndr	0.8890
age_copilot	0.5918
oml_rstrctns	1
ac_model_risk	0.7507
ac_age_risk	0.4415
mel_risk	1
redund_risk	1
prop_rel_risk	0.8037
sys_rel_risk	0.9317
climb_grad	1
reverser	0.5734
antiskid	0.6125
eng_failure	1
prop_failure	0.5261
pres_failure	0.4175
power_failure	1
model_age	0.5576
freq_unexp	1
num_cat_a	1
num_cat_b	0.8160
num_rie	0.6964

4.2.2 Statistical Data and Information Analysis

Most of the input membership functions' definitions in Table 4 and Table 5 were derived using the consultation of aviation experts in CAA Finland. However, some of the definitions needed some further studying and analysing of statistics and applicable certification specifications. These are the propulsion and system failure rates as well as the frequency of unexpected failures in Table 5. The definition of their membership functions are reviewed more closely below.

Propulsion and System Failure Rates

The definitions for engine failure rate's membership functions were derived using Robert E. Breiling Associates' annual accident review 2012 for single turboprop powered aircraft [38], a report of Nall general aviation accidents in 2012 [39] and EASA's rulemaking documents for SET-IMC [4] [6]. At this point, it must be mentioned that, for twin-engined aeroplanes, the same propulsion failure rate definitions are used. In this case, the failure rate applies to the situation, where one of the engines or propellers fails. The distinction to the single-engined aeroplanes emerges in the 'climb gradient in OEI situation' parameter. For single-engined aeroplanes it is equal to the power-off glide ratio (gradient < 0 %) whereas for twin-engined aeroplanes it is specific to the available thrust in OEI situation (gradient ≥ 0 %).

The Breiling's accident review [38] covers all the accidents occurred among U.S. and Canadian registered fleets throughout the aircraft introduction till 2012. The applicable data have been extracted to Table 8.

Table 8. Accident data for various SET aeroplane models. [38]

	CE-208	TBM-700/ TBM-850	PC-12	PA-46-500TP
Fleet size (year end 2012)	878	422	794	363
Hours flown	8 445 005	734 072	2 958 834	575 456
Accidents due power loss / mechanical malf / failure	20	2	4	2
Power loss accident rate per flight hour	$2.4 \cdot 10^{-6}$	$2.7 \cdot 10^{-6}$	$1.4 \cdot 10^{-6}$	$3.5 \cdot 10^{-6}$
Power loss fatal accident rate per flight hour	$0.12 \cdot 10^{-6}$	0	0	0

The Nall report [39] in turn reveals that in 2012 in total 72 power loss accidents occurred to non-commercial fixed-wing aeroplanes registered to U.S. Nine of these were fatal. Over the same time frame, the aeroplanes have flown about 17 768 000 hours. This data results to total and fatal power loss rates of $4.05 \cdot 10^{-6}$ 1/fh and $0.51 \cdot 10^{-6}$ 1/fh, respectively. These numbers include all the aeroplane models and engine types.

In comparison, EASA has established in its SET-IMC rulemaking process [4] [6] a safety target of $1.3 \cdot 10^{-6}$ 1/fh for a fatal accident rate following an engine failure. As a base the agency has used an engine reliability rate of 10 occurrences per million flight hours, which is equal to $1 \cdot 10^{-5}$ 1/fh. Compared to the actual failure rates presented above, this value is too large although the fatal/total accident ratio is fairly realistic (0.51/4.05 versus 1.3/10). To make the risk assessment in this thesis to correspond with the reality, it was therefore decided to use a value $4 \cdot 10^{-6}$ 1/fh as a base, which results to a fuzzy set 'medium'. The whole definition was then configured to be: good < $2 \cdot 10^{-6}$ 1/fh, medium $2\text{-}6 \cdot 10^{-6}$ 1/fh, poor > $6 \cdot 10^{-6}$ 1/fh in a range of $1 \cdot 10^{-6}$-$1 \cdot 10^{-5}$ 1/fh as in Table 5.

Regarding the definitions for propeller failure rate membership functions, EASA's certification specifications for propellers [40] were used as no publicly available studies were found about accidents caused by a propeller failure. These specifications establish a requirement that hazardous propeller effects are not allowed to occur at a rate in excess of that defined as extremely remote (CS-P 150). The definition for this is that the probability of occurrence is $1 \cdot 10^{-7}$ occurrences or less per propeller flight hour. It is also mentioned that this requirement can be complied if it can be predicted that a failure of any of the individual components within the propeller system is more remote than $1 \cdot 10^{-8}$ 1/fh. As a result, it was decided to use a linear scaling between these two values and therefore the definition became: good < $5.5 \cdot 10^{-8}$ 1/fh, poor > $5.5 \cdot 10^{-8}$ 1/fh in a range of $1 \cdot 10^{-8}$-$1 \cdot 10^{-7}$ 1/fh as in Table 5.

The system reliability risk definitions were likewise configured using applicable CS-23 certification specifications [41]. As the pressurisation and electrical power systems can be classified as system components, of which failure would significantly reduce (but not necessary prevent) the capability of the aeroplane or the ability of the crew to cope with adverse operating conditions, the failure probability must be improbable (CS 23.1309). This is equivalent with the term 'extremely remote' and thus the numeric definition is $1 \cdot 10^{-7}$ occurrences per flight hour. Therefore, it was decided to use same definitions for pressurisation and electrical power systems as for the propeller.

The input values for the failure rates should be acquired from the applicable system manufacturer, who has a responsibility to monitor the reliability of its products. However, the author of this thesis was unable to get this data from Pilatus Aircraft Ltd. when inquired. For this reason, only enlightened risk estimates are used in this thesis. In a further development phase of this risk analysis technique, more accurate and model specific failure rates should be used.

Frequency of Unexpected Failures

The definitions for the membership functions of the frequency of unexpected failures were defined using the actual operational data of Hendell Aviation. At the moment of the study, the fleet of Hendell Aviation consisted of two Pilatus PC-12/47E single-engined turbine aeroplanes. The definition for the frequency of unexpected failures is that the failures have occurred unexpectedly in between the maintenance intervals and are discovered by a pilot during a flight operation.

A brief study revealed that the frequencies were lying in range of $0\text{-}104.1 \cdot 10^{-3}$ 1/fh when the operational data of the last three years were studied. The three-year average for the first aeroplane was $50.0 \cdot 10^{-3}$ 1/fh whereas for the other it was $22.5 \cdot 10^{-3}$ 1/fh. Based on the flight hours, the weighted average of these values was then $37.1 \cdot 10^{-3}$ 1/fh.

The study revealed that there was a lot of discrepancy with the results for different years but the results were systematically higher for the other aeroplane although the models were same. It can be therefore concluded that the frequency is distinctly dependent on the individual factors of the aeroplane and the same number does not apply to all aeroplanes of the same model.

Although this brief study was not extensive, it still gave some insight for establishing applicable ranges for the frequency. Also some feedback was received from another European SET operator Voldirect Ltd. that they have had roughly the same amount of failures with their Pilatus PC-12 and Socata TBM-850 fleets. However, they were not able to provide exact operational data so that frequencies were not calculated. As a result, the definition for the membership functions was configured to be: good $< 25 \cdot 10^{-3}$ 1/fh, medium $25\text{-}50 \cdot 10^{-3}$ 1/fh, poor $> 50 \cdot 10^{-3}$ 1/fh in a range of $0\text{-}150 \cdot 10^{-3}$ 1/fh as in Table 5. Nonetheless, this definition should be revised with more extensive data in case this fuzzy evaluation method will be developed in future.

4.3 Establishing Fuzzy Rule Base

The fuzzy rule base was established by a linear regression algorithm as presented in the equation (24). This is the sixth step of the process flowchart in Figure 16. For this process, the membership functions of the consequents must first be determined. It was decided to use range of 1-10 for the output values and this range was divided to 37 membership functions. However, as it was decided to use *Sugeno* system in the assessment, these functions are only plain numbers. Therefore, the equivalent output membership values are 1, 1.25, 1.5, …, 9.75, 10. The reason for such a high number of membership functions is that this way a better resolution is achieved and less rounding must be made to the nearest possible integer.

The rules can then be derived using the priority weights in Table 7 by multiplying each fuzzy set index with the applicable priority weight. However, the index must also be divided with the number of each input's fuzzy sets because otherwise the inputs with a high number of fuzzy sets would artificially have more weight to the output value. Number one must be subtracted from both the nominator and denominator to make the scaling behave correctly and for that reason also the priority weight must be multiplied with number ten so that the nominator would stay positive. A usage example of the equation (24) is illustrated in Table 9 and the corresponding screenshot of the rule editor is presented in Figure 22.

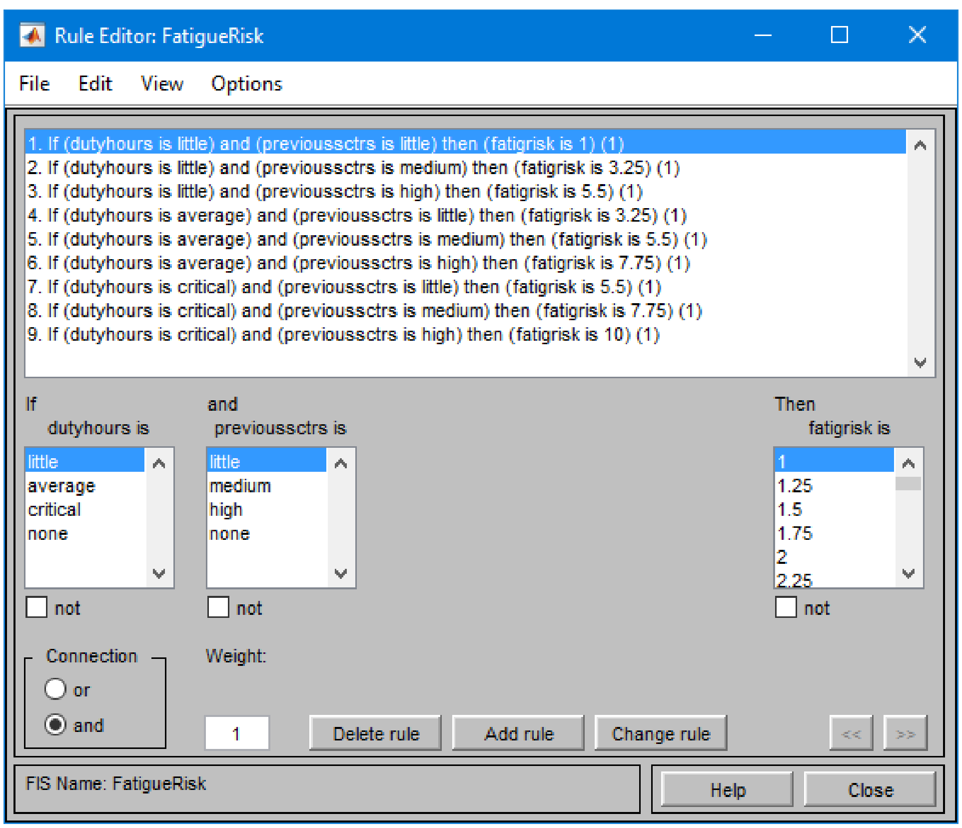


Figure 22. The definition of the fuzzy rule base. Source: MATLAB®.

Table 9. A usage example of the equation (24) for the fatigue risk fuzzy controller.

	Duty hours		Previous sectors	Duty hours (weighted)*	Previous sectors (weighted)**	Sum		Fatigue risk***
	1		1	1.00	1.00	2.00		1
	1		2	1.00	5.44	6.44		10
	1		3	1.00	9.87	10.87		19
	2		1	5.50	1.00	6.50		10
IF	2	**AND**	2	5.50	5.44	10.94	**THEN**	19
	2		3	5.50	9.87	15.37		28
	3		1	10.00	1.00	11.00		19
	3		2	10.00	5.44	15.44		28
	3		3	10.00	9.87	19.87		37

* Calculated with the formula $(1 + (\mathbf{1}\cdot 10 - 1)/(3 - 1))\cdot(A^j_1 - 1))$

** Calculated with the formula $(1 + (\mathbf{0.9871}\cdot 10 - 1)/(3 - 1))\cdot(A^j_2 - 1))$

*** Calculated with the formula $((37 - 1)/(19.87 - 2.00)\cdot(Sum^j - 2.00) + 1)$

In the risk assessment program, this algorithm was implemented as two separate functions. The one function first loads the preprogrammed configuration files (.fis) to the dynamic workspace. The configuration file for each fuzzy controller includes information about all the inputs and outputs, their corresponding ranges and membership functions as well as the number of required rules. However, they are still missing all the consequents in the rules. These are added dynamically to the workspace structure variables during the execution of the program by using the other function. This function basically does the same job as presented in Table 9. The required priority weights are acquired from the function, which handles the eigenvector algorithm. The graphical rule editor in Figure 22 is not needed in the process as all the work is performed on the code level. However, it can be still used to monitor and validate the proper operation of the functions.

It must also be reminded that the rule weights, which are visible in Figure 22, were not used in this algorithm. Basically these weights would scale the effect of the whole rule whereas the priority weights in this assessment affect only to the applicable input of the rule. This way the importance weights of the inputs can be logically directed to the output results of each fuzzy controller. Further validation aspects of this method are presented in Section 5.1.

4.4 Risk Modelling Results

This section introduces some example modelling results using three different hypothetical flight operations, which represent distinct operation classes by their complexity. These are a flight over a highly populated area using major airports as a departure and arrival points, a flight over a congested region using small aerodromes and a flight over an ocean using challenging category C aerodromes. Each assessment is carried out for two different flight crew configurations (low risk and high risk) and three different aeroplane types (twin-engined reciprocating, single-engined turboprop and twin-engined turboprop). The process consists of choosing applicable input values for the assessment (step 7b of Figure 16) and then calculating the results (i.e. step 8 of Figure 16). The hypothetical configurations for the flight crew and airplane are presented in Table 10. The performance related aeroplane parameters have been derived using estimates of aviation experts.

Table 10. The flight crew and aeroplane configurations used in the example modelling.

Risk factor code	Flight crew 1	Flight crew 2
cmndr_total	6000 h	1000 h
cmndr_type	1500 h	100 h
cmndr_recent	120 h	30 h
copilot_total	2200 h	550 h
copilot_type	150 h	20 h
copilot_recent	80 h	10 h
crm_perf	1	3
sop_perf	1	3
duty_hours	4	12
previous_sctrs	0	4
age_cmndr	56	35
age_copilot	30	25
oml_rstrctns	1	2

Risk factor code	Twin reciprocating	Single turboprop	Twin turboprop
climb_grad	0 %	-6.25 %	+8.0 %
reverser	2	1	1
antiskid	2	1	1
eng_failure	$7.2 \cdot 10^{-6}$	$1.4 \cdot 10^{-6}$	$2.5 \cdot 10^{-6}$
prop_failure	$9 \cdot 10^{-8}$	$4 \cdot 10^{-8}$	$4 \cdot 10^{-8}$
pres_failure	$8 \cdot 10^{-8}$	$5 \cdot 10^{-8}$	$1 \cdot 10^{-8}$
power_failure	$8 \cdot 10^{-8}$	$2 \cdot 10^{-8}$	$1 \cdot 10^{-8}$
model_age	45	8	20
freq_unexp	$8 \cdot 10^{-3}$	$37 \cdot 10^{-3}$	$15 \cdot 10^{-3}$
num_cat_a	0	0	1
num_cat_b	1	2	0
num_rie	0	0	1

4.4.1 Scenario 1

The first scenario is a flight from Munich Airport (EDDM) to Paris Charles de Gaulle Airport (LFPG) in the daytime and varying weather conditions. No alternate aerodromes are needed for twin-engined aeroplanes as the flight time is only about 2.1 hours and there are multiple runways available at the departure and arrival (CAT.OP.MPA.180) but for the single-engined aeroplane one additional en-route alternate is needed and it is chosen to be Frankfurt Airport (EDDF). The flight level is chosen to be FL260 for all the cases. For the single-engined aeroplane, the risk period consists of only the take-off phase from 0 ft to 1 000 ft above ground level. This is assumed to take about one minute, which yields a risk period of 0.79 %. For the twin-engined aeroplanes, the risk period is not applicable and therefore it is zero for them. All the sector and environment related parameters regarding this scenario are presented in Table 11.

Table 11. The sector and environment related parameters and their corresponding risk level for the scenario 1.

Risk factor code	EDDM	LFPG	EDDF*
light_systems	1	1	1
appr_systems	1	1	1
circling_min	N/A	600 ft	N/A
airport_elev	1487 ft	392 ft	364 ft
avg_weather	1	1	1
obstructions	2213 ft	2108 ft	3936 ft
perf_limits	1	1	1
rwy_ratio	0.17	0.24	0.17
braking_act	0.42	0.32	0.37
rvr	2.5	1.5	1.8
precipitation	0 mm	8 mm	2 mm
wnd_spd	4 m/s	14 m/s	8 m/s
wnd_drctn	25°	30°	110°
wnd_gust	3 m/s	9 m/s	5 m/s
light_cond	1	1	1
icing	1	1	1
RISK LEVEL	**1.37**	**1.79**	**1.58**

* Applies only to single-engined aeroplanes

As seen in Table 11, worse weather conditions have a noticeable effect on the risk level when comparing EDDM and LFPG. However, the most undesirable wind direction with the combination of highest obstruction level (minimum sector height (MSH)) raises the risk level of EDDF close to the risk level of LFPG although the weather conditions are not as bad for EDDF. The risk levels for the whole flight can be seen in Table 12.

Table 12. The risk levels for the planned flight of the scenario 1 with different flight crew and aeroplane configurations.

	Twin reciprocating	Single turboprop	Twin turboprop
Flight crew 1	2.92	2.49	2.39
Flight crew 2	5.29	4.86	4.76

Table 12 shows that the reciprocating aeroplane results to the highest risk level although it has two engines. The difference between the twin-engined reciprocating and single-engined turboprop aeroplanes is far greater than the difference between the single-engined turboprop and twin-engined turboprop aeroplanes. In percent, the risk increase between the safest and riskiest aeroplane type is up to 18.2 % whereas the risk increase between the low risk and high risk flight crews is up to 49.8 %. Therefore, it can be concluded that the flight crew has far more contribution to the total risk level of a flight than the aeroplane itself.

4.4.2 Scenario 2

The second scenario is a flight from Gällivare Airport (ESNG) to Kirkenes Airport (ENKR) in the daytime and in severe icing conditions. The approximated flight time is 1.5 hours with the flight level FL260. In this scenario, the departure aerodrome is chosen to be also the destination alternate. For the single-engined aeroplane, the en-route alternate is Kaamanen Airfield at 69.125º N 27.235º E. To be more precise, for example Enontekiö Airport (EFET) would have been a better alternate as it has runway lighting and IFR equipment but Kaamanen Airfield was chosen to see the effect of a landing site as an alternate to the overall risk level. Again, the risk period for single-engined aeroplane consists of only the take-off phase from 0 ft to 1 000 ft above ground level so this yields to risk period of 1.11 % by using the one minute assumption. All the sector and environment related parameters regarding this scenario are presented in Table 13. The minimum sector height for the Kaamanen Airfield has been approximated using an online map service.

Table 13. The sector and environment related parameters and their corresponding risk level for the scenario 2.

Risk factor code	ESNG	ENKR	Kaaman.*
light_systems	1	1	-
appr_systems	1	1	-
circling_min	720 ft	798 ft	-
airport_elev	1027 ft	282 ft	-
avg_weather	1	1	-
obstructions	2973 ft	2918 ft	-
perf_limits	1	4	-
rwy_ratio	0.39	0.31	-
braking_act	0.23	0.27	-
obstacles	-	-	1978 ft
gnd_surface	-	-	2
elevation	-	-	498 ft
length	-	-	0.41
width	-	-	30 m
slope	-	-	0º
rvr	3.7	3.0	3.5
precipitation	0 mm	0 mm	0 mm
wnd_spd	7 m/s	5 m/s	8 m/s
wnd_drctn	25º	10º	50º
wnd_gust	2 m/s	4 m/s	3 m/s
light_cond	1	1	1
icing	3	3	3
RISK LEVEL	**2.47**	**2.74**	**5.16**

* Applies only to single-engined aeroplanes

It can be seen that the risk levels for the aerodromes of the scenario 2 (Table 13) are much higher than for the aerodromes of the scenario 1 (Table 11). This is largely caused by the severe icing, shorter runways and worse braking actions. The significantly higher risk level for the Kaamanen Airfield comes from the conservative assumption made in this thesis that a landing site is always riskier than an aerodrome because there's no approach or landing charts published for the landing sites and their properties are not validated, i.e. it is not 100 % confident that the landing site is exactly what is anticipated. For that reason the system is configured so that, without taking into account the environmental aspects, the minimum risk level of a landing site is the maximum risk level of an aerodrome. The risk levels for the whole flight can be seen in Table 14.

Table 14. The risk levels for the planned flight of the scenario 2 with different flight crew and aeroplane configurations.

	Twin reciprocating	Single turboprop	Twin turboprop
Flight crew 1	3.15	2.76	2.63
Flight crew 2	5.55	5.14	5.01

Although the risk levels for the departure and arrival aerodromes have increased up to 40 % for the scenario 2 compared to the scenario 1, the risk levels for the whole flight as in Table 14 have increased only about 6 % because the flight crew and aeroplane configurations have still remained the same. This is a rational outcome as the sector based risks constitute only a part of the total risk. Noticeable is also an observation that the flight with the single-engined turboprop aeroplane is still considerably safer than the flight with twin-engined reciprocating aeroplane although a landing site was used as an en-route alternate instead of an aerodrome.

4.4.3 Scenario 3

The third scenario is a flight from Gibraltar Airport (LXGB) to Ajaccio Napoleon Bonaparte Airport (LFKJ) at night and in a severe crosswind. The total flight time is about 3.0 hours with the same flight level FL260. The Ibiza Airport (LEIB) and Menorca Airport (LEMH) act in this case as en-route alternates for the single-engined aeroplane. LEMH is also chosen to be the destination alternate. This time the risk period consists of both the take-off phase from 0 ft to 1 000 ft above ground level (approximately one minute) and also the en-route phases, where the aeroplane is over 34 minutes away from an aerodrome (refer to Figure 1). In this case, the en-route risk period flight covers roughly 8 minutes. So, in total, the risk period is about 9 minutes of the flight duration of 240 minutes. As a result, this yields to risk period percentage of 3.75 %. For comparison, the calculation was repeated for the flight by using only LEMH as an en-route alternate. In this case the total risk period would be 40 minutes, which yields to risk period percentage of 16.67 %. All the sector and environment related parameters regarding this scenario are presented in Table 15.

Table 15. The sector and environment related parameters and their corresponding risk level for the scenario 3.

Risk factor code	LXGB	LFKJ	LEIB*	LEMH
light_systems	4	4	1	1
appr_systems	3	1	1	1
circling_min	N/A	1100 ft	970 ft	440 ft
airport_elev	12 ft	19 ft	24 ft	302 ft
avg_weather	2	2	1	1
obstructions	6788 ft	10681 ft	2776 ft	2198 ft
perf_limits	1	1	1	1
rwy_ratio	0.38	0.27	0.24	0.31
braking_act	0.45	0.41	0.46	0.47
rvr	2.5	2.7	2.6	2.5
precipitation	0 mm	0 mm	0 mm	0 mm
wnd_spd	15 m/s	16 m/s	14 m/s	13 m/s
wnd_drctn	35°	40°	45°	50°
wnd_gust	4 m/s	2 m/s	5 m/s	5 m/s
light_cond	3	3	3	3
icing	1	1	1	1
RISK LEVEL	**2.39**	**2.27**	**2.07**	**2.07**

* Applies only to single-engined aeroplanes

Compared to the aerodromes of the scenario 2 (Table 13), the risk levels of LXGB and LFKJ (Table 15) are close to the values of ESNG and ENKR. The values of the former are a bit lower because the prevailing lighting conditions have been considered less relevant for the combined risk than icing conditions (see Table 7). Furthermore, for example better braking action and lower airport elevation affect positively to the outcome and seem to partly override worse MSH, RVR and wind conditions. The risk levels for the whole flight can be seen in Table 16. The values in parentheses are for the case of only one en-route alternate along the route (applies to single-engined turboprops).

Table 16. The risk levels for the planned flight of the scenario 3 with different flight crew and aeroplane configurations.

	Twin reciprocating	Single turboprop	Twin turboprop
Flight crew 1	3.08	2.65 (2.67)	2.56
Flight crew 2	5.47	5.02 (5.04)	4.93

The overall results for the scenario 3 as in Table 16 seem also be in the same range with the scenario 2 results (Table 14). Noticeable is an observation for the case of the single-engined aeroplane that dropping out one en-route alternate and replacing it with additional risk period (3.75 % → 16.67 %) has very limited impact to the overall risk. However, by going down the risk hierarchy and examining the output values of the en-route risk node alone reveals that the en-route risk increases up to 20.3 % when the risk period is increased from 3.75 % to 16.67 %.

However, the en-route risk does not affect that much the top level value as both en-route and sector risks are ranked as the least important risk factors in the relevant classes (see Table 7).

4.4.4 Analysis of Risk Modelling

Based on the example modelling, an important conclusion was that the twin-engined reciprocating aeroplane was considered the riskiest by the model as it usually presents an older generation with less safe aeroplane systems. The single and twin-engined turboprop aeroplanes on the other hand were ranked close to each other with only a slight advance for the twin-engined turboprop. However, the used failure rates were mostly rough estimates as no model specific data of each system were available at that moment. Still the results are giving some good direction that single-engined turboprops are almost as safe as twin-engined turboprops and therefore overregulating their operation is inappropriate. Instead, the flight crew related risks were shown to present a considerably stronger role in the combined risk level and, therefore, more emphasis should be given for the development of the flight crew's training.

A closer study of the individual input parameters' behaviour reveals that the effectiveness of the parameter depends on not only its individual weight but also its position in the hierarchy. Therefore, for example commander's age has a stronger influence than commander's total flight hours although the incapacitation risk was weighted significantly less important than the pilot error risk. The reason for this is that the incapacitation risk was modelled to comprise of only three input parameters whereas the pilot error risk comprises of ten input parameters. Therefore, the commander's age has a larger relative fraction to the incapacitation risk value than what the commander's flight hours have to the pilot error risk value. In reality, more parameters are believed to affect the incapacitation risk and for that reason the age of the pilots may have too much influence to the output in this model in reality. It must be noted that the input parameters are rarely totally independent of each other. For example, when a pilot gains age, he concurrently gains more flight experience so the drawbacks of the ageing are often outdone by the increased flight experience.

The technical difficulty of the risk analysis was that the number of nodes on each level was practically limited to a maximum of three as otherwise the number of required rules in the rule base would increase exponentially. Therefore, if more than three child nodes are describing a parent node, an intermediate node is needed to combine some of the child nodes so that the number of nodes on each level remains three or under. This, however, complicates the weighting process and there is a risk that the weights of the child nodes, which were combined with the intermediate node, are underestimated. To ensure that the rearrangement would not have effect to the results, the relative weight of the intermediate node should equal to the sum of its child nodes' weights when all the child nodes are pairwise compared between each other.

5 Evaluation and Validation of Risk Model Results

This section addresses the final step 9 of the process flowchart in Figure 16, that is, the validation of the risk assessment results. This consists of:

1. Determining the rationality and conformity of the model results, and
2. Verifying the acceptability of the results by comparing the values to predetermined safety targets.

5.1 Rationalisation of the Method

The rule viewer of MATLAB® enables a straightforward validation of each fuzzy logic block. For example, Figure 23 shows the rule viewer for the flight crew risk node in an event, where the pilot error risk is 2.8 and the incapacitation risk is 3.5.

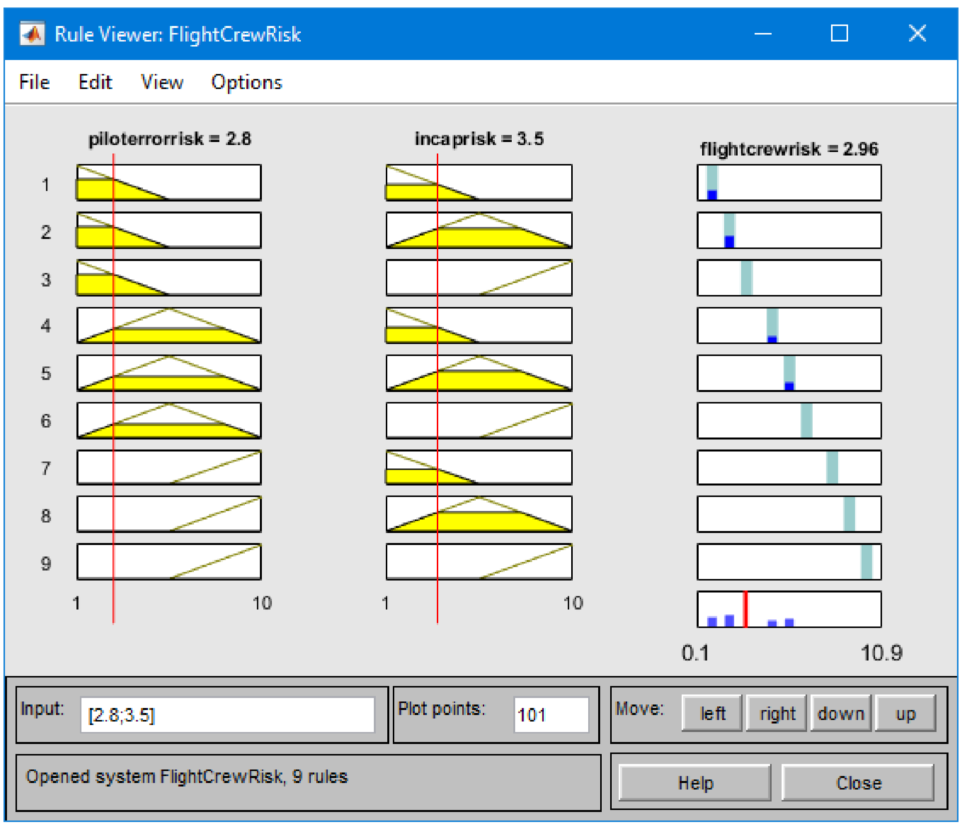


Figure 23. The rule viewer. Source: MATLAB®.

The columns in the rule viewer represent all the inputs and the output. Likewise, each row represents one of the rules and the corresponding membership functions of the fuzzy sets in that rule. The vertical red lines show how the input values settle to their corresponding ranges and how much truth they have in each rule. The truths of the consequents are calculated with the product of the antecedents' truth values. Finally the consequents are combined by calculating the weighted average of all the consequents, where the weights are in this case the truth values of the consequents. The mathematical equations for the membership function in Figure 23 are presented below:

$$\mu_{low}(x_i) = \begin{cases} 0, & x_i \leq 0 \\ x_i, & 0 \leq x_i \leq 1 \\ (5.5 - x_i)/4.5, & 1 \leq x_i \leq 5.5 \\ 0 & x_i \geq 5.5 \end{cases} \tag{26}$$

$$\mu_{medium}(x_i) = \begin{cases} 0, & x_i \leq 1 \\ (x_i - 1)/4.5, & 1 \leq x_i \leq 5.5 \\ (10 - x_i)/4.5, & 5.5 \leq x_i \leq 10 \\ 0 & x_i \geq 10 \end{cases} \tag{27}$$

$$\mu_{high}(x_i) = \begin{cases} 0, & x_i \leq 5.5 \\ (x_i - 5.5)/4.5, & 5.5 \leq x_i \leq 10 \\ (11 - x_i), & 10 \leq x_i \leq 11 \\ 0 & x_i \geq 11 \end{cases} \tag{28}$$

By using the above equations, the truth values, i.e. the firing strengths of each of the antecedents can be calculated. The calculation process conducted in Figure 23 is reproduced in Table 17, which shows all the steps numerically. The truth values of each antecedent and consequent are shown in the parentheses.

Table 17. The calculation process of the fuzzy logic system for the flight crew risk node.

IF x_1 = 2.8	**AND x_2 = 3.5**	
low *(0.600)*	low *(0.444)*	1 *(0.266)*
low *(0.600)*	medium *(0.556)*	2 *(0.334)*
low *(0.600)*	high *(0.000)*	3 *(0.000)*
medium *(0.400)*	low *(0.444)*	4.5 *(0.178)*
medium *(0.400)*	medium *(0.556)*	5.5 *(0.222)*
medium *(0.400)*	high *(0.000)*	6.5 *(0.000)*
high *(0.000)*	low *(0.444)*	8 *(0.000)*
high *(0.000)*	medium *(0.556)*	9 *(0.000)*
high *(0.000)*	high *(0.000)*	10 *(0.000)*
		THEN y = 2.956

The THEN parts in the rule base were determined by using the equation (24) on page 32. In this equation, the pairwise comparison results (Table 7 on page 47) were used in order to get the results to behave realistically with the experts' opinions. In the graphs of Figure 24, the effect of input weighting to the output results can be clearly seen when the same case is compared without and with the weighting.

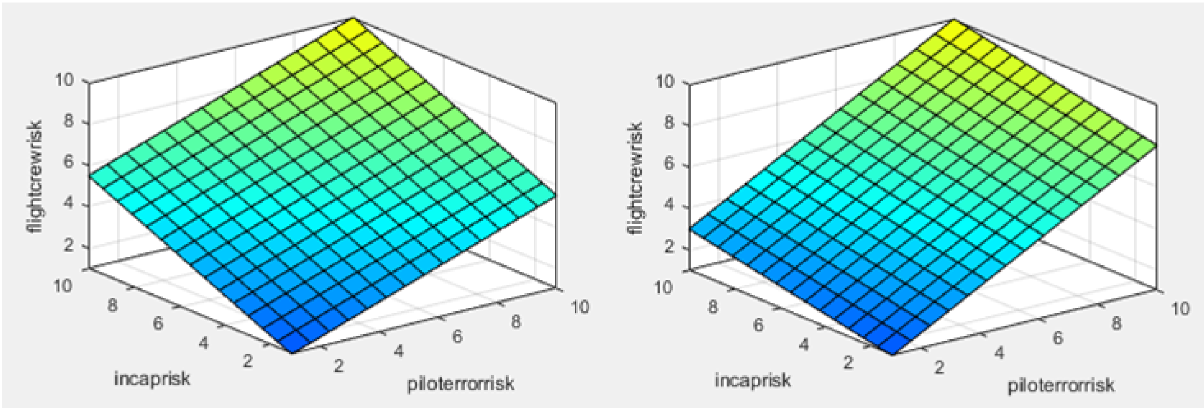


Figure 24. The effect of input weighting on flight crew risk (left without the weighting and right with the weighting).

In the left graph of Figure 24, equal priority weights of 1 and 1 are used for the pilot error and incapacitation risks respectively. For that reason the both edges of the surface graphs are on equal height. This means that the output risk rises to the same level regardless whether the pilot error risk is in its maximum and the incapacitation risk is in its minimum or vice versa. Therefore, both risk factors have a same weight to the flight crew risk level.

However, in the right graph, priority weights of 1 and 0.3512 are used for the pilot error and incapacitation risk respectively (refer to Table 7 on page 47). This results to a situation that the plane of total flight crew risk is tilted strongly to the left. In this case incapacitation risk has far less power to affect to the flight crew risk compared to the pilot error risk. This is consistent with the experts' opinions, which were received via the online survey.

In overall, multiple fuzzy logic blocks similar to the flight crew risk (Figure 23) were linked to each other hierarchically as in Appendix 1 and Appendix 2. Therefore, an output of one block is the input of the other block upper in the risk hierarchy. Each of these blocks has its own set of priority weights established so the outputs of all the fuzzy logic blocks should be rational. As a result, a single output value can be calculated for the whole planned flight with certain departure, alternate and arrival aerodromes. Still the appropriateness of the results should be carefully checked by experts especially in the early validation phase of the method. The hierarchical structures for the models are likely not fully extensive and they do not identify all the possible risk factors and their causal relationships. In the further validation of this analysing technique, these hierarchies should therefore be amended as necessary. Also the definition of the membership functions and priority weights should be revised when more extensive background data is available for utilisation.

5.2 Means to Establish the Safety Limits

5.2.1 Determination of the Airport Category

For the aerodromes of the scenarios 1-3 in Section 4.4, the risk values of the airport category, as in Table 18, were extracted from the developed system.

Table 18. The extracted risk values of the airport category for the aerodromes of the scenarios 1-3.

	Risk value
EDDM	1.47
LFPG	1.57
EDDF	1.69

	Risk value
ESNG	1.79
ENKR	4.53

	Risk value
LXGB	4.68
LFKJ	4.63
LEIB	1.78
LEMH	1.53

The values in Table 18 are different to the results in Table 11, Table 13 and Table 15 as the output of the airport category node is just an intermediate value in the risk model. Only the first seven inputs affect to the risk value of the airport category as seen in Figure 17 on page 37. Therefore, neither the runway condition risks nor environment risks have effect on the definition of the airport category (risk).

It was already known in advance, based on the national AIPs of the airports, that Kirkenes Airport (ENKR) must be dealt as a category B airport and Gibraltar Airport (LXGB) as well as Ajaccio Napoleon Bonaparte Airport (LFKJ) must be dealt as category C airports. The risk values in Table 18 for these airports can be seen to be considerably higher compared to the values of the other airports. Therefore, the results given by the airport category submodel seem to agree with the reality (AIPs).

However, the distinction between the risk values of the above mentioned three airports is not great. It can be thereby concluded that they are verging the border between the category B and C airports. Of course more assessments should be made for a larger variety of airports to get a stronger reference. Based on the data here, the definition for the category C airport is set to be a risk value equal to or larger than 4.60.

The definition for the category B airport is somewhat more challenging to be established as in the above data, only one category B airport exists. Anyhow, all the remaining airports, many of which are large European airports (with a capability to precise category II approaches), have a risk level lower than 2.0 so they can be depicted as category A airports with a good confidence. The definition for the category B airport is thereby set to be equal to or larger than 2.0. It must be noted that this airport category determination submodel is probably not fully compliant with the existing EASA airport categorisation criteria, yet it is, evidently, a better tool to understand the whole picture instead of just making the determination based on only one critical parameter.

5.2.2 Definition of the Acceptance Criteria for the Risk Levels

An essential step, after receiving an output risk level for a planned flight, is the comparison of the results with the criteria, which define the safety limits for flight operations. However, there exist no unambiguous criteria that could readily be set to be applicable. EASA's regulations establish limitations for a few risk factors, which restrain the risk level to some extent, but they are not sufficient enough to establish uniform risk level limits. Moreover, different operators fly different nature of operations and, therefore, the mean risk level for each operator often varies.

For the above reasons, it is more reasonable to examine typical risk values for a couple of operators conducting various different operation types and establish the safety limit based on the data. In this case, the risk level can be considered unacceptable if it differs 'enough' from the representative average value. To establish this average value, a longer-term validation phase should be conducted to calculate a risk value for a representative sample of flights over certain time period and check whether normal distribution is a good model of variation between operators. A mean risk value and standard deviation should then be calculated based on the distribution of the results. A sample size as large as practically possible should be used to mitigate the standard error. Then the safety limit can be set to a point, which differs from the mean distribution with a 0.01 confidence level. This means that 99 % of all the flights have a risk value lower than this threshold value. However, a risk value of 5.5 (middle point of the output range) should not be exceeded in any case regardless of the mean value. This is also supported by the analysis result here that the value of 5.5 is near the ultimate maximum risk value (of the scenarios in Section 4.4).

In addition to the risk values of the planned flight, the risk values of the departure, arrival and alternate points should also be checked individually so that they are not too excessive. If the prevailing weather conditions for some aerodrome or landing site are too poor to be coped with by taking into account the individual properties of that aerodrome or landing site, then this aerodrome or landing site can be considered too dangerous to be operated. In this case, an excessive risk cannot be compensated by low risk values of the flight crew and aircraft branches. The establishment of the safety limits for the aerodromes and landing sites should be implemented using the same principles as described above for the planned flight. Mean values and standard deviations should be established for a group of typical aerodromes and typical landing sites respectively and if the risk value for some aerodrome or landing site exceeds significantly the mean distribution, e.g. with a 0.01 confidence level, then another operating point should be chosen.

In overall, the following steps should be conducted to determine the acceptability of a planned flight:

1. Ensure that all the flight parameters are within the limitations of Airplane Flight Manual and EASA's regulations.
2. Compare the calculated risk level of the planned flight with the safety limit. Make sure that the value remains under the limit.
3. Check that all published aerodrome and airspace minimums are complied.
4. Check that the risk level of each aerodrome (and landing site if used) does not exceed the applicable safety limit.
5. If any of the calculated risk value is over the limit, look for possible means to mitigate the risk. See section 6.

6 Risk Mitigation Measures

In case that any of the risk assessment results are considered excessive, some mitigation actions must be conducted in order to get the assessment results remain within acceptable limits. This is done by modifying the layout of the flight so that the values of certain parameters move to a more favourable direction. However, many of the individual parameters are not directly controllable by an operator. For example, the risk factors forming a risk level for an aerodrome cannot be 'altered' without changing the runway or entire location.

When it is concluded, based on the results, that risk mitigation is needed, the challenging issue is to determine which risk factors should be 'modified' by changes in operation to reach the safety target. Figure 25 shows for example the effect of cruise altitude and risk period to the overall risk level in the case of the scenario 3 for a single-engined aeroplane (in Section 4.4.3). The graphs are produced by changing the applicable parameter while leaving the other parameters untouched and then recalculating the result. The vertical axis shows the change of the risk level when the risk factor is shifted from a low risk to high risk level. The nonlinear shape of the cruise altitude curve comes from the definition of the membership functions; the risk level is more sensitive to altitude changes at low flight levels as most weather phenomena affect at low altitudes (higher probability). The slope of the risk period curve is considered to be constant instead.

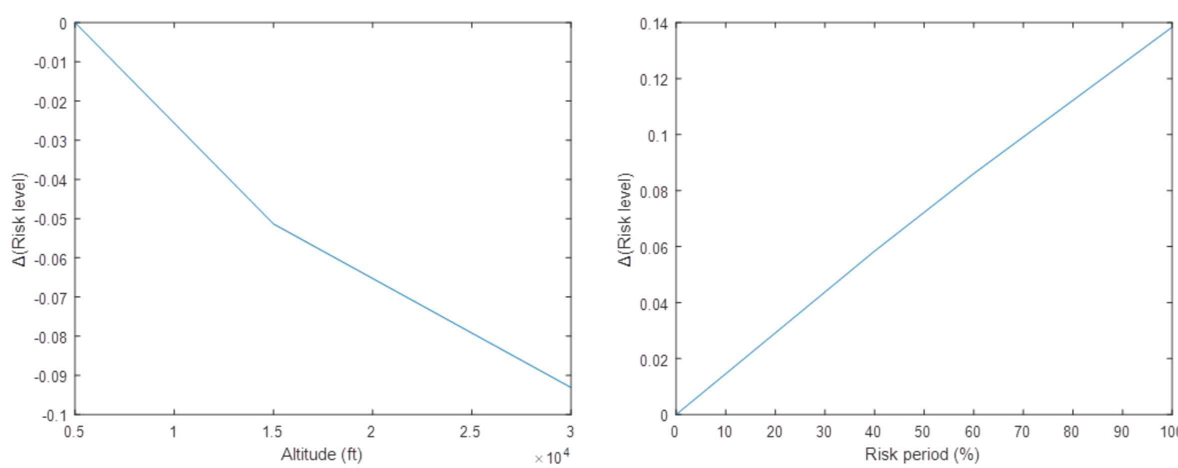


Figure 25. The effect of the cruise altitude and risk period to the overall risk level of the planned flight.

The total impact of the cruise altitude and risk period to the overall risk level is rather limited as shown in Figure 25. The influence of an individual risk factor on the overall risk level depends on how much weight has been given to the risk factor and in which level in the hierarchy the risk factor lies. The leaves up in the hierarchy have primarily strong influence as their local effects are not split so many times in subsequent fuzzy logic blocks. Table 19 shows the total influence of each individual risk factor to the overall risk.

Table 19. The total influence of each individual risk factor to the overall risk.

Input code	Influence
length	1.3117
obstacles	1.1111
icing	0.9028
gnd_surface	0.8025
slope	0.7716
width	0.6944
light_cond	0.6250
rvr	0.4591
elevation	0.3704
rwy_ratio	0.3657
braking_act	0.2963
perf_limits	0.2546
precipitation	0.2160
avg_weather	0.1260
obstructions	0.1260
appr_systems	0.1157
wnd_drctn	0.1125
light_systems	0.1003
wnd_gust	0.0900
airport_elev	0.0810
wnd_spd	0.0675
circling_min	0.0617

Input code	Influence
crm_perf	0.7298
sop_perf	0.6529
num_cat_a	0.6250
num_cat_b	0.5000
duty_hours	0.4321
previous_sctrs	0.4321
num_rie	0.4167
oml_rstrctns	0.3704
freq_unexp	0.3333
age_cmndr	0.3210
power_failure	0.2500
age_copilot	0.1975
eng_failure	0.1852
climb_grad	0.1836
cmndr_total	0.1760
cmndr_type	0.1760
model_age	0.1667
cmndr_recent	0.1614
risk_period	0.1505
copilot_recent	0.1214
antiskid	0.1080
altitude	0.1042
copilot_total	0.1027
copilot_type	0.1027
reverser	0.0972
prop_failure	0.0926
pres_failure	0.0833

The left side tabulation in Table 19 shows the influence of a risk factor on the aerodrome and landing site determination model and the right side tabulation the influence on the flight planning model. The influence of each individual risk factor is calculated by first setting all the risk factors to their minimums so that the system outputs a risk level of 1.0 and then adjusting one risk factor at a time to its maximum. However, because of the nonlinear nature of fuzzy inference system, the influence of each risk factor is not constant (as in Table 19). When the risk factors are interfering together, their influences slightly overlap and can therefore vary. This is caused by the fact that there is a limited number of possible consequences in the rule base and, therefore, the weighted sum of the antecedents must be rounded to the nearest possible consequent.

Table 19 gives some insight about the means to mitigate a risk effectively. For example, it can be concluded that the development of operator's CRM and SOP has the most positive impact on the risk level. On the other hand, the failure rate of the pressurisation alone has a small impact as it is only a single factor of the aircraft model risk.

7 Summary and Conclusions

The objective of this thesis was to make a research about different kind of risk analysis methods used in the aviation field and find suitable means to develop new kinds of risk models for the field of flight planning in commercial operation of performance class B aeroplanes. More specifically, the case examples concerned the risk analysis of aerodrome and landing site determination and flight planning. In total, ten analysis methods were reviewed and of these, the weighted hierarchical modelling technique and fuzzy rule-based analysis method were chosen for further utilisation. As a result, two different weighted fuzzy hierarchy models were developed. In addition, the models were linked to each other so that the aerodrome and landing site determination model complements the flight planning model. The models consisted of 80 risk nodes in total, of which 49 nodes were leaves that took the input values into the system. The nodes were then connected to each other using 30 fuzzy inference blocks in total.

The effectiveness of the weighted fuzzy hierarchy models is primarily based on the utilisation of expert judgement instead of pure accident data. Yet, the model is still complemented with the information about aircraft systems' failure rates. The expert judgement is applied in multiple phases, which include the identification of the risk factors, forming their hierarchical structure and establishing the importance weights and membership functions of the inputs. Particularly challenging in the process is the establishment of justified importance weights for each risk factor as the evaluation is highly dependable of subjective opinions per each expert. In this thesis, this issue was avoided by gathering opinions from multiple experts using a pairwise comparison method and then calculating a geometric average of all the responses. Although the standard deviation of the responses was relatively high, the results seemed to be rational. With the weighting, the risk factors considered more important could be emphasized in the model so that the output is more dependent on their values.

The high level use of expert judgement in the risk analysis was based on the principle that proactive assessment method should be preferred instead of relying on reactive interpretation of accident statistics (alone). Often, an accident is a result of one or two main causes, which are then aggravated by multiple further events. The key factor is to proactively identify all the individual risk factors, which might contribute to an accident to happen, and find their causal relationships. This way, the flights having higher potential to end up in an accident can be determined based on the assumption that they also more likely contain more adverse risk elements in their operation conditions. Finally, although the weighted fuzzy hierarchy model only determines how much risk factors are present during a flight, it also indirectly determines the likelihood of an accident for that flight.

The results of the risk analysis proved to be rational and realistic. Three distinct scenarios were introduced in Section 4.4 to illustrate different operational conditions based on geographical locations, aerodromes' properties and environment conditions. The model logically gave the lowest risk level for the defined scenario 1 as it was a flight over an inhabited area using large category A airports. The risk level rose for the defined scenario 2 when severe icing was present and smaller aerodromes were concerned with less runway length available and worse braking action. Also, the performance limitations of the arrival aerodrome had discernible effect on the risk level. Still, the result for the defined scenario 3 wasn't as high as for the scenario 2 although most challenging category C airports were concerned at night and in severe crosswind. The explanation for this was that these drawbacks were overridden by other aspects and that icing was not present and therefore the braking action was also better.

The most prominent distinction between the results of example flights was caused by the variation of flight crew related parameters. The difference in the results was up to 50 % depending on whether the low risk or high risk flight crew configuration was used. This result can be easily justified as most aviation accidents are caused by pilot errors. Moreover, a closer study revealed that the quality of the pilot training and operating procedures had most influence in the risk analysis and their importance cannot therefore be underestimated. The type of the operated aeroplane had also a moderate effect on the results with up to 18 % relative difference.

In the original research questions defined in Section 1.2, the influence of the risk period (single-engined aeroplanes) and the cruise altitude to the overall exposed risk were to be solved. According to Figure 25 on page 65, the effects were illustrated to be rather limited as they represent only two single factors of the total 49 input parameters. It is challenging to calculate a single percent value to describe the risk variation as it is not constant in every configuration due to the nature of the fuzzy logic system. Based on the data in Table 19 on page 66, estimates of 1.4 % for the cruise altitude and 2.1 % for the risk period are given. However, for single-engined aeroplanes, these parameters are not totally independent of each other as lowering the cruise altitude may also increase the risk period in certain circumstances. If assumed for example that a single-engined aeroplane is flying over an open sea, where no en-route alternates exist, the risk period increases with the same rate as the cruise altitude is decreased.

The objective of the thesis was also to determine and validate the risk factors concerning an emergency landing site. In the risk model, six input parameters were used to describe the applicability of a landing site. These were obstacles, surface, elevation, length, width and slope of the runway. Moreover, it was assumed that the base risk level of a landing site is the maximum risk level of an aerodrome risk when no environment risks are taken into account. This was rationalised with the fact that, typically, a landing site is not originally meant for aircraft operation and no up-to-date information is available about its current condition. Because of the latter reason, the validation of risk factors is a challenge. If no other available means are available, the operator should visit the place on a regular basis and confirm the appropriateness of the place to be used as an en-route alternate. However, it was earlier calculated that a typical single-engined aeroplane can glide up to 34 minutes from FL260 to 1 000 ft AGL after engine failure. Because of this, there are not many places in Europe, where landing sites should actually be addressed.

The risk models still need further development and validation before they could be accepted to the actual operator use as the risk models are still rather simplified and experimental. The models calculate the risk level based only on the risk factors they identify. Many more complicated aspects, which can have effect to the actual risk, are still excluded. For example, the flight crew's familiarity with the chosen aerodromes may also have an influence to the pilot error risk. In addition, no further indicators were yet developed to the flight planning model to measure the actual effectiveness of the crew resource management and standard operating procedures. It is therefore challenging to determine which kinds of procedures are factually efficient.

Finally, the targets established for this thesis were reached. A new tool was developed to quantify the selections made upon the flight planning process and to calculate their corresponding risk level. Some risk mitigation means were also introduced and it could be showed that the risk can be greatly mitigated especially by improving flight crew related parameters. Moreover, the type of the operated aeroplane had a distinct effect on the output and modern redundant aeroplanes should therefore be preferred. The method also proved to be efficient in the airport categorisation process and it showed that the results were consistent with existing EASA's criteria.

The following steps are suggested to be conducted in the further development process of the flight planning risk models:

1. Amend the hierarchies with more branches,
2. Develop the definitions of the membership functions,
3. Revise the weights of the risk factors,
4. Validate the appropriateness of the results with practical experiments,
5. Define the safety limits for the flight operations, and
6. Develop the graphical user interface for the risk analysis.

This thesis showed that the weighted fuzzy hierarchy method as a technique is efficient in the risk analysis process and therefore it is recommended to be applied it to other cases besides the flight planning. As CAA Finland has recently transferred to risk-based approach to manage their activities and resources, it is worth to study the implementation of the weighted fuzzy hierarchy method.

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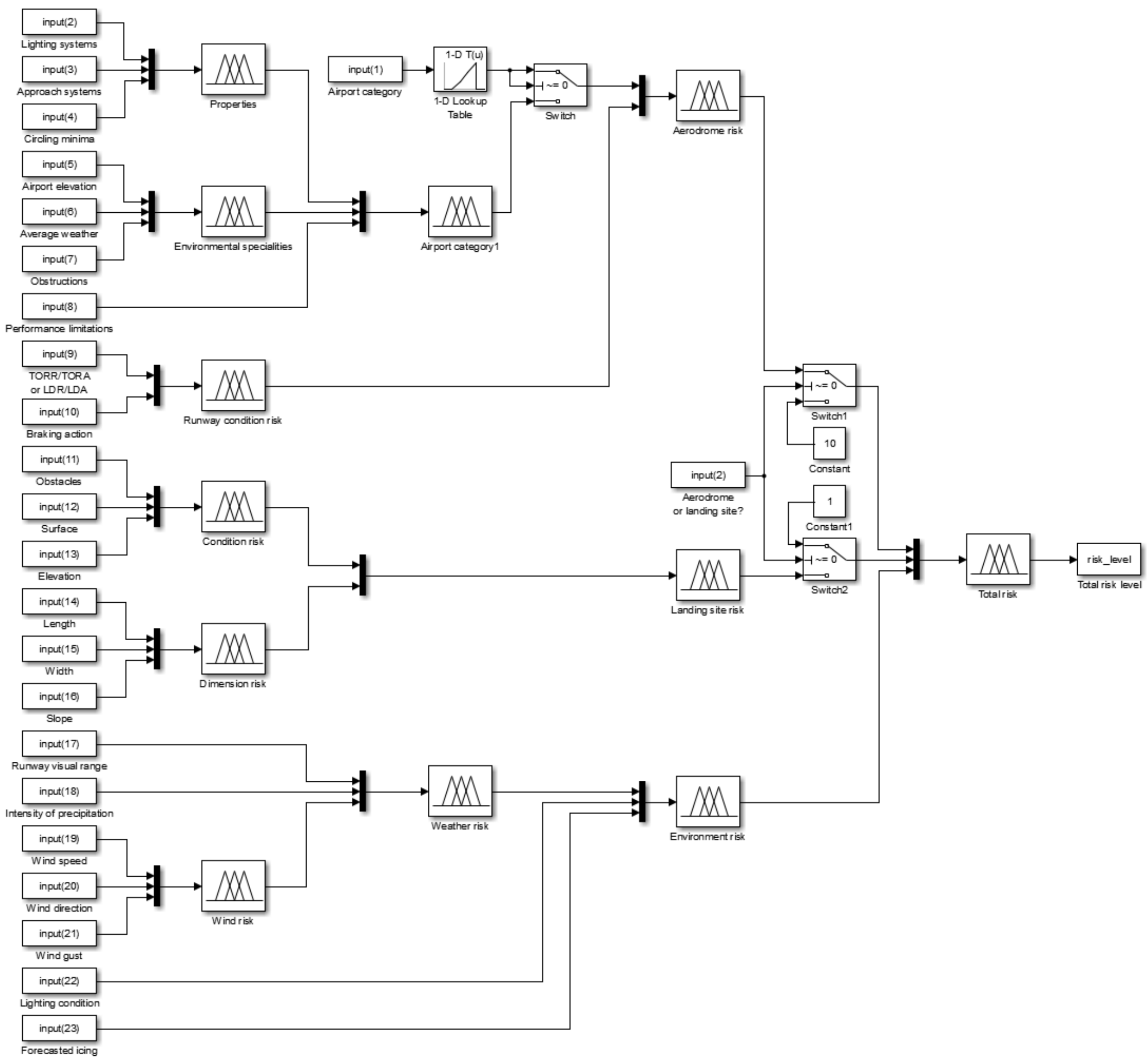
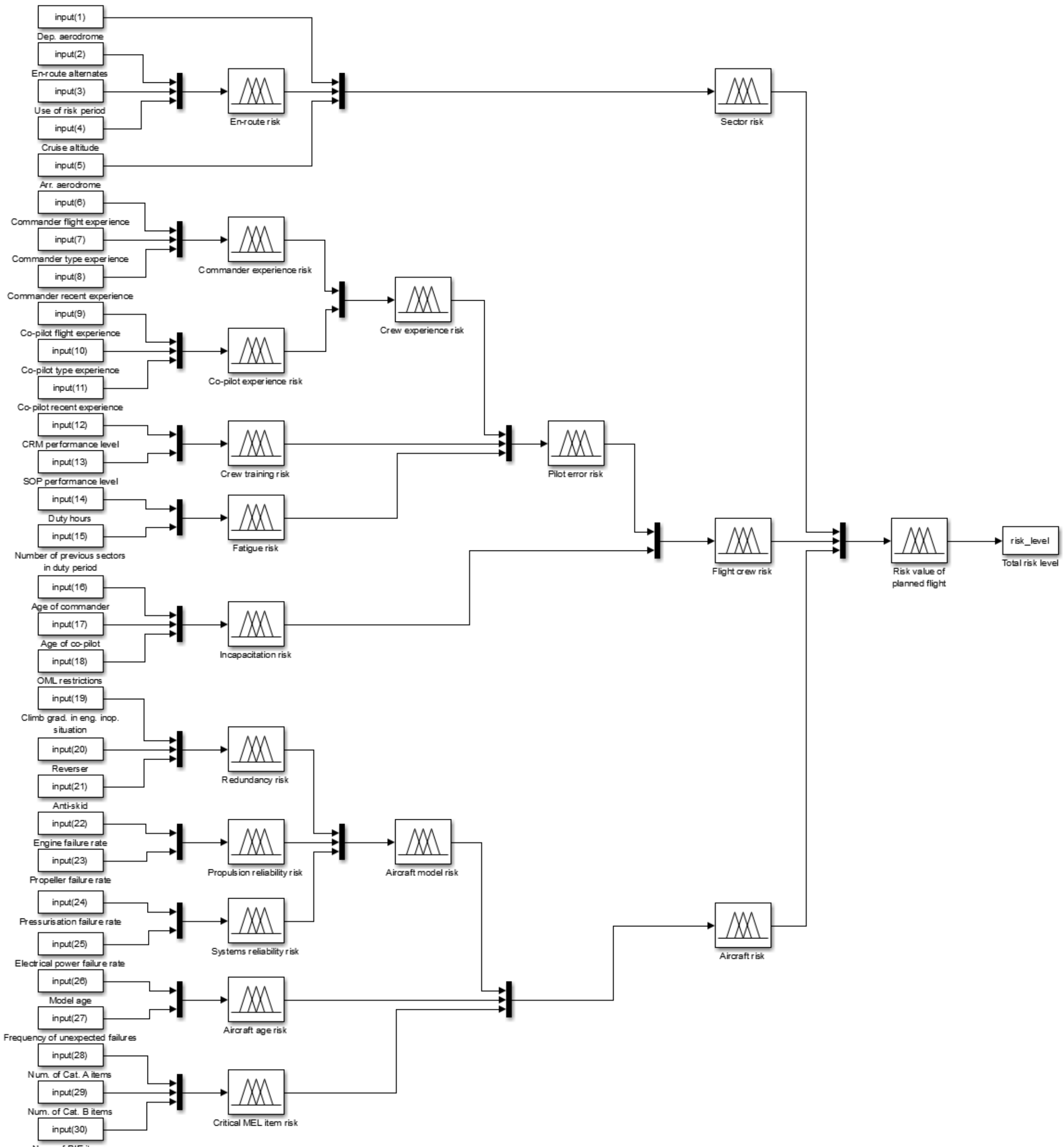
Appendices

Appendix 1 Simulink Model of Aerodrome and Landing Site Determination



Appendix 2 Simulink Model of Flight Planning



Appendix 3 Weight Ratio Matrices of Aerodrome and Landing Site Determination

	aerodrome_risk	lnd_site_risk	environ_risk
aerodrome_risk	1,0	0,3	0,8
lnd_site_risk	3,3	1,0	1,4
environ_risk	1,3	0,7	1,0

	airport_cat	rwy_cond_risk
airport_cat	1,0	1,3
rwy_cond_risk	0,7	1,0

	properties	environ_spec	perf_limits
properties	1,0	0,8	1,1
environ_spec	1,3	1,0	1,1
perf_limits	0,9	0,9	1,0

	light_systems	appr_systems	circling_min
light_systems	1,0	0,9	1,6
appr_systems	1,1	1,0	1,9
circling_min	0,6	0,5	1,0

	airport_elev	avg_weather	obstructions
airport_elev	1,0	0,7	0,7
avg_weather	1,5	1,0	1,0
obstructions	1,4	1,0	1,0

	rwy_ratio	braking_act
rwy_ratio	1,0	1,2
braking_act	0,8	1,0

	cond_risk	dimen_risk
cond_risk	1,0	0,8
dimen_risk	1,2	1,0

	obstacles	gnd_surface	elevation
obstacles	1,0	1,5	2,3
gnd_surface	0,7	1,0	2,0
elevation	0,4	0,5	1,0

	length	width	slope
length	1,0	1,9	1,5
width	0,5	1,0	1,1
slope	0,7	0,9	1,0

	weather_risk	light_cond	icing
weather_risk	1,0	1,7	1,0
light_cond	0,6	1,0	0,8
icing	1,0	1,3	1,0

	rvr	precipitation	wind_risk
rvr	1,0	1,8	1,6
precipitation	0,6	1,0	0,7
wind_risk	0,6	1,4	1,0

	wnd_spd	wnd_drctn	wnd_gust
wnd_spd	1,0	0,6	0,8
wnd_drctn	1,6	1,0	1,1
wnd_gust	1,3	0,9	1,0

Appendix 4 Weight Ratio Matrices of Flight Planning

	sector_risk	flight_crew_risk	aircraft_risk
sector_risk	1,0	0,8	0,7
flight_crew_risk	1,2	1,0	1,7
aircraft_risk	1,4	0,6	1,0

	departure	enroute_risk	arrival
departure	1,0	2,1	0,7
enroute_risk	0,5	1,0	0,4
arrival	1,5	2,4	1,0

	enroute	risk_period	altitude
alternate	1,0	1,1	1,4
risk_period	0,9	1,0	1,4
altitude	0,7	0,7	1,0

	pilot_error_risk	incap_risk
pilot_error_risk	1,0	2,8
incap_risk	0,4	1,0

	crew_exp_risk	crew_tr_risk	fatig_risk
crew_exp_risk	1,0	0,7	0,9
crew_tr_risk	1,5	1,0	1,4
fatig_risk	1,1	0,7	1,0

	cmndr_exp_risk	copilot_exp_risk
cmndr_exp_risk	1,0	1,4
copilot_exp_risk	0,7	1,0

	cmndr_total	cmndr_type	cmndr_recent
cmndr_total	1,0	1,2	0,9
cmndr_type	0,9	1,0	1,3
cmndr_recent	1,1	0,8	1,0

	copilot_total	copilot_type	copilot_recent
copilot_total	1,0	1,3	0,7
copilot_type	0,8	1,0	1,1
copilot_recent	1,5	0,9	1,0

	crm_perf	sop_perf
crm_perf	1,0	1,1
sop_perf	0,9	1,0

	duty_hours	previous_sctrs
duty_hours	1,0	1,0
previous_sctrs	1,0	1,0

	age_cmndr	age_copilot	oml_rstrctns
age_cmndr	1,0	2,1	0,7
age_copilot	0,5	1,0	0,8
oml_rstrctns	1,5	1,2	1,0

	ac_model_risk	ac_age_risk	mel_risk
ac_model_risk	1,0	1,7	0,7
ac_age_risk	0,6	1,0	0,5
mel_risk	1,4	2,2	1,0

	redund_risk	prop_rel_risk	sys_rel_risk
redund_risk	1,0	1,1	1,2
prop_rel_risk	0,9	1,0	0,8
sys_rel_risk	0,9	1,3	1,0

	climb_grad	reverser	antiskid
climb_grad	1,0	1,6	1,8
reverser	0,6	1,0	0,9
antiskid	0,6	1,2	1,0

	eng_failure	prop_failure
eng_failure	1,0	1,9
prop_failure	0,5	1,0

	pres_failure	power_failure
pres_failure	1,0	0,4
power_failure	2,4	1,0

	model_age	freq_unexp
model_age	1,0	0,6
freq_unexp	1,8	1,0

	num_cat_a	num_cat_b	num_rie
num_cat_a	1,0	1,3	1,3
num_cat_b	0,7	1,0	1,3
num_rie	0,8	0,8	1,0